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Essays on Mutual Funds

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Dedicated to my parents.

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Essays on Mutual Funds

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This dissertation is composed of two empirical studies on mutual funds. Chapter 1 studies the implication of the timing of mutual fund entry for subsequent long-term fund performance. As fund companies choose when to open new funds and what investment styles they practice, these choices may be informative about the fund qualities. I empirically explore the relation between entrant fund performance and past style performance. By examining a sample of 2,801 mutual fund entrant during the period of 1991–2015, I find that entrant funds with investment styles that have recently performed well tend to underperform in the future. The post-entry performance of hot style entrants is worse than both the post-entry performance of cold style entrants and the concurrent performance of incumbents in the same style categories. The empirical findings are unlikely to be driven by stock-level return reversals or competition among mutual funds, but consistent with fund investors practicing style investing and extrapolating their beliefs on style returns, leading to lower entry thresholds for fund managers in hot investment styles.

Chapter 2 includes my joint work with David Xiaoyu Xu on how regulations in the Chinese stock market can affect investor behavior in the mutual fund market. We show that trading suspension, a regulatory policy on stock trading activities, gives rise to stale mutual fund NAVs and indirectly affects fund investors' behavior. Using a sample of 3,205 long-term trading suspension events in China during 2004–2018, we find that opportunistic investors combine firm-specific news and fund portfolio reports to make investment decisions. Quarterly fund flows positively respond to suspended portfolio stocks' unrealized impact on fund NAVs. Such responses are stronger for impactful good news, and portfolio disclosure plays a key role in this mechanism. Our findings suggest the need for a better integrated financial regulatory framework in emerging markets.

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Chapter 1

Style Timing and Performance of Mutual Fund Entrants

1.1 Introduction

The U.S. mutual fund industry has seen enormous growth in the past few decades. Mutual funds have become an important investment vehicle for U.S. households to manage their financial wealth.[1] While investors nowadays have thousands of mutual funds to choose from, hundreds of new funds are still opened each year.[2] Given the plethora of choices of funds and the churning in the industry, one might wonder if we could learn anything about the properties of newly opened funds based on their entry decisions.

In this study, I attempt to offer an angle to take on the above question by studying the connection between the timing of fund entry and the performance of newly offered funds. Just like firms considering launching new products need to decide on the specifications of the products and the timing of entry, mutual fund companies also endogenously choose what types of funds to offer and when to offer them. Understanding whether the entry decision made by fund companies reveals how funds perform in the

[1] According to the Investment Company Institute (ICI), the total net assets managed by mutual funds grew from USD 134.8 billion in 1980 to USD 17.7 trillion in 2018. Collectively, U.S. households put 21% of their total financial wealth in mutual funds at year-end 2018.

[2] There are 8,078 mutual funds at year-end 2018. 345 are newly opened in 2018.

future could potentially help investors make better investment decisions, and inform us about what drives the industry dynamics.

As a theoretical starting point, in a perfectly competitive market for mutual funds, if investors are fully rational (Berk and Green, 2004), then fund performance should be unrelated to the timing of fund entry. New funds are offered when fund companies expect them to perform well enough to attract sufficient investor flows such that the expected fee revenue would cover the cost of setting up and running the funds, justifying the entry decision. Rational investors would competitively supply capital flows to new funds such that they always expect to earn zero net alpha. Therefore, post-entry performance of entrant funds would not depend on the timing of entry.

However, the premise that investors are fully rational has already been challenged by a ripe literature on behavioral economics. Several aspects of the field are particularly relevant and applicable to the context of investment in mutual funds. First, people often group situations or objects into coarse categories to make inferences (Mullainathan, 2002). Investors may categorize risky assets into different styles and make allocations among styles based on their relative attractiveness (Barberis and Shleifer, 2003). In the market for mutual funds, it is natural for investors to categorize funds into styles when making investment decisions. Mutual funds often advertise their investment strategies in terms of different investment styles such as small-cap, large-cap, value, and growth. Fund names usually also reflect the investment styles adopted by the funds, or the industry sectors their strategies focus on.[3] In addition, analytical tools widely used by

[3]For example, the prospectus of Fidelity Small Cap Value Fund (FCPVX) states the following in its five-bullet-point description of its principle investment strategies: "investing at least 80% of assets

fund investors, such as Morningstar and Lipper, present data and market information on mutual funds to users by classifying funds into different style categories.

Second, investors form beliefs by extrapolating their recent past experiences.[4] When considering a newly opened fund that belongs to a particular style category, investors may be too optimistic about its expected future performance because funds in that style category have generally performed well recently. Incorporating these two simple and reasonable behavioral elements into the theoretical analysis gives rise to interesting deviations from the implications of the rational benchmark. Investors' thinking in categories implies that the entry threshold for funds is specific to each fund style category rather than common to all funds. Further, their extrapolative beliefs lead to a link between past style performance and style-specific entry thresholds. New funds in a style category would effectively face a lower entry threshold in terms of their true abilities to generate abnormal returns if the recent style performance has been high.

I formalize my intuition in a simple competitive equilibrium model that incorporates the two behavioral elements, and contrast its implications to those of the rational benchmark. While the benchmark model implies time-invariant entry threshold and ir-

in securities of companies with small market capitalizations" and "investing in securities of companies that Fidelity Management & Research Company (FMR) believes are undervalued in the marketplace in relation to factors such as assets, sales, earnings, growth potential, or cash flow, or in relation to securities of other companies in the same industry (stocks of these companies are often called "value" stocks)".

[4]For example, Smith, Suchanek, and Williams (1988), Barberis, Greenwood, Jin, and Shleifer (2018), and Haruvy, Lahav, and Noussair (2007) emphasize the relation between extrapolative beliefs and asset bubbles, Barberis, Shleifer, and Vishny (1998), Altı and Tetlock (2014), and Barberis, Greenwood, Jin, and Shleifer (2015) study asset pricing implications of extrapolative beliefs. Lakonishok, Shleifer, and Vishny (1994), La Porta (1996), La Porta, Lakonishok, Shleifer, and Vishny (1997), and Benartzi (2001) find empirical evidence consistent with overextrapolative expectations. Greenwood and Shleifer (2014) present survey evidence for extrapolative expectations.

relevance of timing of entry for fund performance, the alternative model generates style- and time-specific entry threshold and predicts negative correlation between post-entry fund performance and past style performance.

The empirical content of this chapter focuses on testing the relation between entrant fund post-entry performance and past style performance in the sample of U.S. active equity funds opened between 1991 and 2015. Using stock characteristics of initial fund holdings to classify entrant funds into different style categories, I find a negative correlation between the post-entry performance of entrant funds and the past performance of their styles. In particular, funds opened at times when their styles are hot on average underperform by around one percentage point per year in the first three years following fund inception compared to funds in the same style categories but opened during cold periods. When the magnitude of past style performance is considered, the average annual post-entry performance in the first three years is around 20 basis points lower for entrant funds when the annual style return adjusted for market return is one percent higher in the past two years.

One potential alternative explanation for the lower post-entry fund performance for entrant funds in episodes following high past style performance could be the well-documented return reversal effect at both the stock-level and the style-level (De Bondt and Thaler, 1985; Teo and Woo, 2004; Kumar, 2009). The increased intensity of competition among funds in the same style category due to newly opened funds may also be a reason for the observed underperformance (Wahal and Wang, 2011; Hoberg, Kumar, and Prabhala, 2017). Although it is reasonable to believe that both alternative mechanisms could be at play in this context, they are supposed to affect both the entrant and the

incumbent funds in the same style category in the same manner. To distinguish from these explanations, I further examine whether the difference between the performance of entrant and incumbent funds in the same style category are related to past style performance, and again find a negative correlation. This lends credibility to the entry threshold effect that is expected to only affect entrant funds as a separate mechanism that causes underperformance of hot style entrant funds.

The contribution of this work nests under a large literature devoted to understanding the investment management skills of mutual funds (Wermers, 2000; Fama and French, 2010) and investment performance earned by fund investors (Malkiel, 1995; Gruber, 1996; Zheng, 1999). The novelty of this study is that it focuses on the extensive margin of fund entry. By relating fund entry decision to performance of entrant funds, it proposes a mechanism through which market conditions can shift the distribution of investment skills and performance of existing funds, and provides consistent empirical evidence.

This study draws insights from and builds upon studies on style investing (Barberis and Shleifer, 2003; Teo and Woo, 2004; Cooper, Gulen, and Rau, 2005; Froot and Teo, 2008; Kumar, 2009; Boyer, 2011). However, none of the existing studies have linked past style performance to fund performance through the effect of fund entry decisions.

On the subject of fund entry, Khorana and Servaes (1999) examine the determinants of mutual fund openings and find that the recent performance of funds with a particular investment objective, among other factors, is positively associated with likelihood of future fund openings in that investment objective. However, they do not further explore the implications of this determinant on the subsequent performance of entrant

funds. Two other papers also share this study's focus on the performance of newly opened funds. De Souza (2019) finds that new funds that hold popular stocks at birth tend to underperform. Chuprinin and Ruf (2017) find that new funds that invest heavily in past winner stocks tend to underperform. My study differs from these two in that I examine the relation between style-level returns, rather than stock returns, and entrant performance, hence raising a distinct mechanism to explain entrant fund performance.

In Section 1.2, I construct a model to formalize the intuition that leads to the main hypothesis of the chapter. Section 1.3 describes the data used for the empirical analysis in detail. Section 1.4 presents the main empirical findings. Robustness checks are included in Section 1.5. Section 1.6 presents additional findings that explore alternative notions of investment styles and hotness of styles. Section 1.7 concludes.

1.2 Model

This section presents a simple model of fund entry to illustrate the intuition behind the hypotheses in this chapter. The model adopts from the canonical competitive partial equilibrium model for mutual funds and fund investors (Berk and Green, 2004). The main extension to the original model is that I separate the component of fund performance due to managers' investment abilities from that due to average style performance. This allows me to consider the role of fund style and the relation between model outcome and style performance. I first introduce the framework of the model, and then consider two different assumptions on investor beliefs. In the first case, I assume investors are fully rational. In the second, investors are assumed to have extrapolative beliefs on style performance. I analyze and contrast the model implications on fund

entry decisions and post-entry fund performance in both cases.

1.2.1 Model Setup

Consider a model with two dates, $t \in \{0, 1\}$. At date $t = 0$, a group of fund managers with different investment management abilities, a^m, drawn from a distribution F, arrive at the market as potential entrants. Each of them, knowing her own ability, decides whether to open a new fund that operates for one period by incurring a one-time fixed setup cost of C upfront. Investors allocate their money to funds after fund entry decisions are made at $t = 0$. The fund receives a fixed management fee f for each dollar it manages at $t = 0$, and will be liquidated at $t = 1$.

1.2.1.1 Fund Alpha

The gross alpha generated by a fund, r_{t+1}, is determined by the following production function:

$$r_{t+1} = a^m + a^s_{t+1} - bq_t, \tag{1.1}$$

where a^m is manager's investment ability, a^s_{t+1} is the average performance of the fund's investment style s, b is a positive constant that captures decreasing returns to scale (Berk and Green, 2004; Chen, Hong, Huang, and Kubik, 2004; Lewis, 2015; Harvey and Liu, 2017), and q_t is the fund's assets under management at date t. The separation of the terms a^m and a^s_{t+1} distinguishes the component of fund alpha due to the manager's superior stock-picking ability from that due to the investment style adopted by the fund (Daniel, Grinblatt, Titman, and Wermers, 1997; Wermers, 2000). In addition to managers' abilities to pick stocks, some investment styles may on average perform better

than others during certain periods. I capture this additional component of alpha production by adding the time-varying style performance term a^s_{t+1}. The style performance component in fund alpha varies over time and is assumed to be *i.i.d.* with zero mean, i.e., $\mathbb{E}_t[a^s_{t+1}] = 0, \forall t$.

1.2.1.2 Investor Flow

As in Berk and Green (2004), the supply of investment talent is scarce and investors competitively allocate their capital to mutual funds. In equilibrium, investors expect to earn zero net alpha from their investment. Using $\mathbb{E}^I_t[\cdot]$ to denote investors' expectation at t, we have

$$\mathbb{E}^I_t[r_{t+1}] - f = \mathbb{E}^I_t[a^m] + \mathbb{E}^I_t[a^s_{t+1}] - bq_t - f = 0. \tag{1.2}$$

This zero net alpha condition due to competitive supply of capital determines the equilibrium size of a fund at date t:

$$q_t = \frac{\mathbb{E}^I_t[a^m] + \mathbb{E}^I_t[a^s_{t+1}] - f}{b}. \tag{1.3}$$

1.2.1.3 Entry Threshold

The entry decision hinges on whether a potential entrant expects to earn sufficient fee revenue to cover its initial fixed cost:

$$q_0 f \geq C. \tag{1.4}$$

Substituting the equilibrium fund size in (1.3) into (1.4), we have the entry condition:

$$\mathbb{E}^I_0[a^m] \geq \frac{bC}{f} + f - \mathbb{E}^I_0[a^s_1]. \tag{1.5}$$

In equilibrium, investors' expectation for managers' abilities, $\mathbb{E}_0^I[a^m]$, should be the conditional mean of those managers who choose to enter. This implies an entry threshold for manager ability, a^{m*}, which solves the following equation (1.6) such that all mangers with higher abilities will find it profitable to enter the market.

$$\mathbb{E}[a^m | a^m \geq a^{m*}] = \frac{bC}{f} + f - \mathbb{E}_0^I[a_1^s]. \tag{1.6}$$

Note that investors' beliefs about the style performance appear on the right-hand side of (1.6) and will have an influence on the determination of the entry threshold for manager abilities.

1.2.2 Rational Benchmark

Given the framework above, I first consider the implications for fund entry and entrant performance under the assumption that investors are perfectly rational. Rational investors correctly perceive that the style performance component has no persistence, i.e., $\mathbb{E}_0^I[a_1^s] = 0$. Immediately, (1.6) becomes

$$\mathbb{E}[a^m | a^m \geq a^{m*}] = \frac{bC}{f} + f. \tag{1.7}$$

In this case, the entry threshold a^{m*} does not depend on style performance. Substituting $\mathbb{E}_0^I[a^m] = \mathbb{E}[a^m | a^m \geq a^{m*}]$ and $\mathbb{E}_0^I[a_1^s] = 0$ into (1.3), the equilibrium fund size at $t = 0$ is

$$\begin{aligned} q_0 &= \frac{\mathbb{E}[a^m | a^m \geq a^{m*}] + \mathbb{E}_0^I[a_1^s] - f}{b} \\ &= \frac{C}{f}. \end{aligned} \tag{1.8}$$

The average post-entry net alpha earned by fund investors is

$$\begin{aligned}\mathbb{E}[r_1|a^m \geq a^{m*}] - f &= \mathbb{E}[a^m|a^m \geq a^{m*}] + \mathbb{E}[a_1^s] - bq_0 - f \\ &= \frac{bC}{f} + f - b \cdot \frac{C}{f} - f \\ &= 0.\end{aligned} \tag{1.9}$$

As in the canonical Berk and Green (2004) model, rational investors on average earn zero net alphas from their investment in mutual funds.

The following proposition summarizes the model implications on fund entry and post-entry performance under the rational benchmark.

Proposition 1. *If investors have rational beliefs, the fund entry threshold, a^{m*}, and the average post-entry fund performance do not depend on past style performance, a_0^s.*

1.2.3 Extrapolative Beliefs on Style Performance

Now suppose investors are not fully rational, and they believe that the expected profitability of an investment style would continue to be high (low) if they observe high (low) past style performance. In other words, investors over-extrapolate the style-level performance. To capture this, I assume that investors believe that style performance is persistent, i.e., $\mathbb{E}_t^I[a_{t+1}^s] = \theta a_t^s$, where $\theta \in (0, 1)$ is a constant that captures the persistence perceived by investors. In contrast to the previous subsection where investors are rational, now the substitutability of manager ability and style profitability in the gross alpha production function (1.1) implies that the entry threshold for manager ability will be lower when investors believe that the style is going to continue its recent high

performance. To see this, substitute $\mathbb{E}_0^I[a_1^s] = a_0^s$ into (1.6):

$$\begin{aligned}\mathbb{E}[a^m|a^m \geq a^{m*}] &= \frac{bC}{f} + f - \mathbb{E}_0^I[a_1^s] \\ &= \frac{bC}{f} + f - \theta a_0^s.\end{aligned} \tag{1.10}$$

Note that style performance in the period prior to $t = 0$, a_0^s, appears on the right-hand side of (1.10). The solution for a^{m*} is smaller when a_0^s is larger. Compared to the rational benchmark, the entry threshold now depends on the style s adopted by the potential entrant, and is lower when the past performance of the style is higher. Applying (1.3), the equilibrium size of entrant funds at $t = 0$ is

$$\begin{aligned}q_0 &= \frac{\mathbb{E}[a^m|a^m \geq a^{m*}] + \mathbb{E}_0^I[a_1^s] - f}{b} \\ &= \frac{\frac{bC}{f} + f - \theta a_0^s + \theta a_0^s - f}{b} \\ &= \frac{C}{f}.\end{aligned} \tag{1.11}$$

The average post-entry net alpha earned by fund investors is

$$\begin{aligned}\mathbb{E}[r_1|a^m \geq a^{m*}] - f &= \mathbb{E}[a^m|a^m \geq a^{m*}] + \mathbb{E}[a_1^s] - bq_0 - f \\ &= \frac{bC}{f} + f - \theta a_0^s - b \cdot \frac{C}{f} - f \\ &= -\theta a_0^s.\end{aligned} \tag{1.12}$$

Although the equilibrium fund size in (1.11) is the same as that in the rational benchmark, investors no longer earn constant zero net alpha on average. Instead, the average post-entry fund performance depends on past style performance, and is lower when past style performance is higher. This difference from the rational benchmark is mainly driven by the difference in the entry threshold a^m, which leads to difference in the $\mathbb{E}[a^m|a^m \geq a^{m*}]$ term. When past style performance is high, the entry threshold is

lower, making it easier for managers with lower abilities to open new funds and expect to break even. Hence, the average manager ability is lower for cohorts of entrants following a time period when style performance is high. These cohorts of new funds on average perform worse in the future.

Proposition 2 states the relation between entry threshold and past style performance under the assumption of extrapolative beliefs.

Proposition 2. *If investors have extrapolative beliefs on past style performance, the fund entry threshold a^{m*} and the average post-entry performance of entrant funds are both decreasing in the past style performance a_0^s.*

1.2.4 Model Conclusion

The analyses of the model under different assumptions about investor rationality show how fund entry and post-entry fund performance may be related to fund style and past style performance. In the rational benchmark, the entry threshold for manager abilities and post-entry fund performance do not depend on the timing of entry with regard to recent past style performance. When investors have biased extrapolative beliefs about future style performance, the entry threshold is lower for an investment style if the style has recently performed well, which leads to lower average manager ability for the cohort of entrants with that investment style. Consequently, these entrants on average perform worse in the future. In the remainder of this chapter, I study empirically whether the performance of entrant funds into a fund style has a negative correlation with past style performance.

1.3 Data

1.3.1 Sample Construction

The sample of mutual funds used for empirical analyses is constructed by combining data on fund return and characteristics from CRSP, and fund holdings data from both Thomson Financial and CRSP. The coverage of the initial sample begins in 1980, for which holdings data is first available, and ends in 2018. I start by including funds in CRSP that have investment objective codes designated by data vendors indicating that they invest primarily in U.S. equity securities, and discarding index funds.[5] This sample is then merged with Thomson Financial holdings database using MFLINKS available from WRDS. Several researchers have found that the Thomson holdings database has quality and coverage issues for the later part of the sample period, especially after 2008 (Shive and Yun, 2013; Zhu, 2019). Therefore, for funds that are initially selected from CRSP but do not have a valid match in the Thomson database, I further look for holdings information in the CRSP holdings file and include the linked data points in my sample when available.[6] These selection criteria result in 5,282 unique funds with returns, characteristics, and holdings data available from 1980 to 2018.

The date of entry for a fund is identified as the date when the first share class of the fund series is offered.[7] To construct a sample of entrant funds, I further require

[5] Funds that have Lipper class codes in 'EIEI', 'LCCE', 'LCGE', 'LCVE', 'MCCE', 'MCGE', 'MCVE', 'MLCE', 'MLGE', 'MLVE', 'SCCE', 'SCGE', 'SCVE', Strategic Insight objective codes in 'AGG', 'GMC', 'GRI', 'GRO', 'ING', 'SCG', or Wiesenberger objective codes in 'SCG', 'G', 'LTG', 'MCG', 'GCI', 'G-I' are considered as equity funds. A fund is regarded as an index fund if the CRSP variable *index_fund_flag* equals 'D' (pure indexing), or if its name contains "index", "dow", "s&p", or "nasdaq".

[6] Appendix A.1 provides further details for this procedure.

[7] Section 1.5.1 explores alternative ways to measure fund entry date.

that a newly established fund has at least one holdings snapshot available within the first 24 months following its inception date. This requirement is to ensure that my holdings-based style classification can reliably measure the style category of the fund perceived by investors at the time of fund inception. The full sample of entrant funds starts from 1982 because the main empirical analyses uses style performance in the past two years to determine the hot and cold status of style category at the time of fund entry. The sample ends in 2015 to allow for at least 3 years of post-entry observation for fund performance evaluation. These restrictions leave me with a sample of 2,927 entrants from 1982 to 2015.

The first four columns in Table 1.1 display the number of incumbent funds and entrant funds in the sample. The mutual fund industry experienced rapid growth in the 1990s. Annual numbers of entrants dwindled during the years around the financial crisis in 2008, but have recovered to about 100 entrants per year since then.

1.3.2 Holdings-Based Investment Styles

I classify funds into a set of investment style categories based on the average characteristics of their stock holdings. This approach is consistent with both academic research and industry practice. Motivated by the relation between stock characteristics and the cross-sectional variation in stock returns (Daniel and Titman, 1997), Daniel, Grinblatt, Titman, and Wermers (1997) propose using characteristic-sorted stock portfolios as benchmarks for mutual fund performance evaluation. Likewise, analysts and investors in the industry often use Morningstar style boxes to categorize fund investment styles when evaluating their performance.

I use the two most widely recognized dimensions of stock characteristics, size and book-to-market, to categorize fund investment styles. Mutual funds often describe their investment strategies in terms of these two dimensions, and many adopt names to directly reflect how their investment strategies are tilted on these two dimensions. In the literature on style investing, other empirical studies also primarily focus on the these two style dimensions (Chan, Chen, and Lakonishok, 2002; Teo and Woo, 2004; Cooper, Gulen, and Rau, 2005; Froot and Teo, 2008; Kumar, 2009) and use them to designate styles for stocks.

Following Daniel, Grinblatt, Titman, and Wermers (1997), in July of each year, I assign all stocks listed on NYSE, AMEX, and Nasdaq into 5×5 bins by first dividing them into five groups based on NYSE market capitalization quintile breakpoints, and then sorting each group into quintiles by their Fama-French 48 industries-adjusted book-to-market ratios. Each stock receives a size score range from 1 (small) to 5 (large) and a book-to-market score from 1 (growth) to 5 (value). The style scores for stocks are maintained for the next 12 months until they are calculated again in the next July. For each fund holding snapshot observed, I calculate the value-weighted average size score and book-to-market score for the effective date of the holdings observation. In each year, I sort the incumbent funds by their size scores and book-to-market scores calculated from their first holdings observations within the year, and compute the 33rd and 67th percentile cutoffs on for both scores. The size score cutoffs are used to assign incumbent and entrant funds into small, mid, and large size categories. Similarly, the book-to-market score cutoffs are used to assign funds into growth, blend, and value categories. At any point of time, a fund in the sample is assigned one of the nine

investment styles that combines the two dimensions of classifications. For example, if an entrant fund's size score falls between the 33rd and the 67th percentile of the size scores, and its book-to-market score is below the 33rd book-to-market score percentile of the incumbents, it will be considered as a mid growth fund at entry.

Using the style classifications, Table 1.1 further breaks down the number of entrant funds in the sample by their investment styles for each year. Casual observation suggests that the proportions of funds introduced in different, especially opposing, styles vary over time. There are notably more growth funds than value funds opened in most years in the 1990s. After 2000, however, more value funds are introduced in the early 2000s, suggesting that the popularity of value compared to growth styles have shifted during this period. The change in the landscape of mutual fund styles during this period is likely related to the rise of internet stocks in the 1990s and the following burst of tech bubble around 2000.

Although data availability permits the entrant fund sample to span the period from 1982 to 2015, the first few years in the sample account for a relatively small number of fund entries. Most years from 1982 to 1990 see less than 20 entrant funds per year. The detailed breakdown of the sample by style categories shows that there is no entrant funds in some style categories during this period. Since this imbalance of observations among years in the sample may affect the precision of statistical inference from some of the empirical tests, I focus on the sample period of 1991–2015 for inference and interpretation in the main body of this chapter. This subsample includes 2,801 out of 2,927 entrant funds of the full sample. The full results of the same tests using the full 1982–2015 sample are reported in Appendix A.2.1 for completeness.

1.4 Results

1.4.1 Performance of Entrant Funds in Hot and Cold Styles

The primary mission of the empirical exercise is to test whether there is a negative correlation between the performance of entrant funds and the past performance of their investment styles. I start by comparing the post-entry performance of hot style entrant funds and that of cold style entrant funds. An investment style is considered as hot at a particular time if the difference between the TNA-weighted average return of all funds in that style category in the past 24 months and the return on the value-weighted CRSP index over the same time window is above the time-series median for the entire sample. This definition of hot versus cold style is meant to capture the time-series variation of attractiveness specific to each style. Entrant funds are classified as hot or cold style entrants based on whether the investment styles they initially adopt are hot or cold at the time of their entries.

1.4.1.1 Two-Sample t-Test

Panel A of Table 1.2 shows the distribution of the number of hot and non-hot entrants across different style categories. Overall, 1,463 out of 2,801 entrant funds are considered hot style entrants. Across different style categories, there are generally more fund entries when the style is hot, except for Large Blend and Large Value.

To measure the post-entry performance, I calculate the average fund return over the value-weighted CRSP index return, the CAPM alpha, the Fama-French 3-factor alpha, and the Cahart 4-factor alpha over the 36-month window following the fund in-

ception date.[8] If a fund is terminated within the first 36 months following the fund inception date, it would still be kept in this sample to avoid survivorship bias as long as there are enough return observations to calculate all of the above measures. Panel B to E of Table 1.2 compare various performance measures between hot and non-hot style entrants and report the results of two-sample t-tests. When all funds are considered, hot style entrants on average perform worse than cold style entrants by all four performance measures. The performance differences are statistically and economically significant. The difference in average performance between hot and cold entrants is around 8 basis points per month measured by CAPM alpha, and around 6 basis points per month measured by 3-factor or 4-factor alpha. Breaking down the sample by style categories reveals more details on the comparison between hot and cold style entrants within each investment style. The differences in performance are negative for the majority of style categories, and are never statistically significant when they are positive. It is noteworthy that the underperformance of hot style entrants tend to be more prominent for investment styles oriented towards small-cap and growth strategies.

1.4.1.2 Regression Tests

The two-sample t-tests help to shed light on within style category comparisons but treat each subsample separately and estimate standard deviation of fund performance differently in each subsample. To draw a better inference on the full sample while focusing on the entry timing effect by comparing funds in the same style category that

[8] The month of fund entry is excluded from the calculation even if monthly return is available for that month.

enter the market at different times, I next turn to a regression approach that includes style fixed-effects. Table 1.3 reports the results of a battery of regressions of post-entry fund performance measured over 12-, 24-, 36-, and 60-month windows on a dummy variable indicating whether a fund enters the market when its style is in hot status. Style fixed-effects are included in all specifications to focus on the entry timing effect on subsequent fund performance within style categories. For statistical inference, I cluster standard errors by style-year groups. This method of clustering accounts for potential correlation among residuals in performance for entrants that enter the same style at the same time.[9] Across all specifications, the regression coefficients suggest that hot style entrants significantly underperform cold style entrants, and the performance difference is about 8 to 10 basis points per month on average.

The dichotomy between hot and non-hot styles seems to suggest that funds that enter the market when their styles have recently performed relatively well tend to perform worse in the future. While using a hot style dummy variable is straightforward, the actual magnitude of style performance, in addition to whether or not it is above the sample median, should also help explain the performance of entrant funds. I repeat the previous regression analyses using the style-level returns, measured by the TNA-weighted average return of incumbent funds in the style category in the previous 24 months in excess of the value-weighted CRSP index return, as the independent variable. The findings reported in Table 1.4 confirm that hot style entrant funds on average perform worse than non-hot style entrants. For example, the 4-factor alpha of a fund is on average 20 basis points lower in the first 3 years following fund entry compared to another fund in the same style

[9] Appendix A.2.2 provides a more detailed discussion on the choice of clustering method.

category if the former enters the market when the style-level performance is 1 percentage point higher. The empirical patterns suggest that funds that enter the market when their styles have recently performed well on average perform worse following entry.

1.4.1.3 Returns on Buy-and-Hold Portfolios of Hot and Cold Style Entrant Funds

Instead of treating each entrant funds in the sample as an independent observation, an alternative approach to comparing performance of hot and cold style entrant funds is to compare performance of buy-and-hold portfolios of hot and cold style entrant funds. Each entrant fund is added to the hot style portfolio or the cold style portfolio in the month following its inception and held for 5 years or until the month it is closed, whichever is earlier. Table 1.5 reports the results of using time-series regressions to compare the performance of hot and cold style buy-and-hold portfolios adjusted for exposure to Carhart four factors. For both equally weighted and value weighted portfolios, the hot style portfolio has lower alpha than the cold style portfolio. Interestingly, hot style portfolio also seems to have lower loading on the HML factor and higher loadings on the SMB factor, consistent with the notion that hot style funds tend to tilt towards growth and small-cap styles. The statistical significance for the underperformance of hot style portfolio is stronger for value weighted portfolios, suggesting that underperformance is more prominent among hot style entrant funds that managed to attract larger investor flows.

1.4.2 Performance of Entrant Funds Relative to Incumbent Funds

While the thesis of this chapter intends to interpret the negative correlation between entrant fund performance and past style performance as evidence for differences in investment skills between hot and cold style entrants, there might be two alternative explanations. One possible driving force underlying this correlation is the well-established empirical observation of return reversal for stocks (De Bondt and Thaler, 1985), and more relevantly, for stocks that belong to certain style categories (Teo and Woo, 2004; Kumar, 2009). The negative correlation presented in the previous section could emerge because funds in a style category inherit the return properties of stocks they hold. Another possible explanation is that fund entries increase the intensity of competition among funds that share similar investment styles and invest in stocks with similar characteristics, thereby making it more difficult for funds in a style category to achieve good performance (Wahal and Wang, 2011; Hoberg, Kumar, and Prabhala, 2017).

Both alternative explanations, the stock-level return reversal mechanism and the competition mechanism, should apply to both entrant funds and incumbent funds, and neither has different implications for the performance of these two groups of funds. In contrast, if the negative correlation is at least partially driven by the lower entry threshold when a style is in a hot period, as is proposed by this study, the difference between average performance of entrant funds and that of incumbent funds should also be negatively related to recent style performance.

To investigate whether this entry threshold channel is at play, I repeat the regression analyses in the previous section by replacing the dependent variable with the difference between entrant fund performance and the TNA-weighted average performance

of incumbent funds in the same style category. Tables 1.6 and 1.7 report the results and show that the post-entry performance of entrant funds compared to their incumbent peer funds is worse when fund entries occur during hot style periods. This finding could not be attributed to stock return reversal or increasing fund competition since these two mechanisms are supposed to affect entrant and incumbent funds in similar manners. Instead, it is consistent with the notion that entry threshold for funds in hot styles is lower and cohorts of funds that enter the market during hot style periods are on average less skillful in generating abnormal performance compared to their incumbent peers.

1.5 Robustness

1.5.1 Fund Incubation and Fund Entry Date

The determination of fund entry date is an important empirical task in this study as the exact timing of the entry may change whether a fund is treated as a hot or cold style entrant. One potential issue with the identification of fund entry date is fund incubation. Evans (2010) points out that a mutual fund may voluntarily choose to operate for a period of time to build return records before deciding to offer the fund to public investors. In the main analyses, I use fund inception date, i.e., *first_offer_dt* in the CRSP database, as fund entry date. As Evans (2010) suggests, this variable may reflect the date when a fund starts incubation instead of when it becomes available to public investors. This will perhaps introduce errors to my measure of fund entry date, determination of hot and cold style entrants, and post-entry fund performance. To address this concern, I repeat the main empirical tests using the 1996–2006 subsample,

for which Evans (2010) shares data[10] on fund ticker creation dates that can be used as proxies for actual dates when funds become public.

For the 1,293 entrant funds in the 1996–2006 subsample, Table 1.8 shows the distribution of the length of fund incubation period, measured by the time lag between the date of fund inception and the date of ticker creation. Over half (669) of them created ticker symbols within one month after the funds start operation. About another one-third (396) created ticker symbols within the first year following fund inception. The remaining 228 funds that created tickers more than 12 months after fund inception are likely incubated funds.

To compare the results using the two different definitions for fund entry date, I first perform the t-tests for the difference between hot and cold entrant performance using the fund inception date as the entry date for the 1996–2006 subsample. The results are reported in Table 1.9. This subsample test reasserts the main findings that hot style entrant underperform cold style entrants. I then use the ticker creation date as the fund entry date and repeat the same tests and report the results in Table 1.10. When using ticker creation dates as entry dates, Panel A of Table 1.10 show that more funds are classified as hot style entrants. This is consistent with the notion that fund companies strategically choose to open incubated funds to public at times when market conditions are more favorable. Panels B, C, and D of Table 1.10 shows that the findings that hot style entrants underperform is robust to excluding incubation period from the analysis. On average, the 36-month Carhart alphas of hot style entrants are lower by 0.12%

[10]This data can be found in the Internet Appendix for Evans (2010) at `https://afajof.org/wp-content/uploads/files/supplements/Internet_Appendix_for_Mutual.xls`.

per month. The differences are negative across most style categories, except for large growth and large blend. Similar to the baseline, the findings of underperformance are most prominent for small- and growth-oriented styles. Table 1.11 further demonstrates the robustness using regressions of post-entry fund performance on the hot style dummy variable. The sizes of the regression coefficients are larger in the baseline, but the magnitudes are still similar. Overall, excluding incubation periods leads to more funds considered as hot style entrants, and the findings that hot style entrants perform worse than cold style entrants is robust to this empirical issue.

1.5.2 Exclusion of Fund Returns in the Early Stage

The fund returns in the early periods following fund inception may not be particularly indicative of fund quality. Fund companies may strategically devote more resources to nascent funds or allocate favorable IPO placements to these funds to help the new funds grow in the early stage. Although this study's main empirical tests focus on fund performance measured over periods of reasonable lengths such as three or five years so that the results are unlikely driven by early period fund returns, I further show that the main results are robust to this concern by excluding the returns in the first year following fund inception from calculation of post-entry fund performance. Table 1.12 shows the comparison of hot and cold entrant fund performance over 36 month starting from the 13th month after fund inception. The results are similar compared to Table 1.2. Table 1.13 reports results on regressions of post-entry fund performance skipping the first year returns on the hot style dummy variable. The results are also similar to the findings in Table 1.3, both in statistical significance and magnitude of coefficients. Although the

differences are small, skipping the first year returns yields slightly larger absolute values for the coefficients, suggesting that fund performance in the first year are on average better than longer-term fund performance.

1.5.3 Look-Ahead Bias in Determination of Hot and Cold Styles

In the main specification, the definition of hot style dummy variable compares the style performance in the past 24 months with the median for the entire sample, which utilizes future information not available at the time of the observation. To address concerns on this look-ahead issue, I use the cumulative median of past 24-month rolling window style performance as the cutoff for definition of hot style dummy variable. The distribution of hot and cold entrants are slightly different as shown in Panel A of Table 1.14. Nonetheless, the overall comparison of post-entry performance of hot and cold entrants, as well as the comparison within each style category, are consistent and similar to the previous findings in Table 1.2. The regressions of post-entry fund performance on this new hot style dummy variable also deliver similar results in Table 1.15 compared to the previous findings in Table 1.3. In particular, the coefficient estimates suggest that the three-year 3-factor or 4-factor alphas of hot entrants are lower by about one percentage point per year on average, similar to the baseline results.

1.5.4 Use Alpha to Measure Style Performance

I previously use style returns in excess of market returns to measure style performance. This simple measure captures investors' perception of the attractiveness of an investment style adjusting for the overall market condition. But this choice should not

drive the main findings of this study. I repeat the main tests that are used to establish the negative correlation between entrant fund performance and past style performance by using 24-month rolling CAPM alpha as the measure of style performance. Tables 1.16, 1.17, and 1.18 report the results of the t-tests, the regressions of post-entry performance on the hot style dummy variable, and the regressions of post-entry performance on past style alpha, respectively. The results are similar to the previous findings. In Table 1.18, the sizes of coefficients are somewhat larger than those in Table 1.4. Given that the standard deviation of style alpha (0.40% per month) is slightly smaller than the standard deviation of style excess return (0.42% per month), the economic magnitudes of hot entrant underperformance in the sample implied by these coefficients are comparable.

1.5.5 Alternative Sorting Methods to Categorize Fund Styles

1.5.5.1 Dependent Sort on Size and Book-to-Market Styles

The previous findings rely on classifying funds into size and book-to-market styles by independently ranking their respective style scores. I show that the main findings are robust to using dependent sort to form style categories. To assign fund styles, I first determine their size category using the 33rd and 67th percentile of the size scores in the cross section, and then determine their book-to-market category using the 33rd and 67th percentile of the book-to-market scores within each size group. Using this style assignment, I repeat the two-sample t-tests for post-entry fund performance for hot and cold style entrant funds and report the results in Table 1.19. Notice that the number of observations are more evenly distributed across the nine style bins. Similar to the previous findings, hot style entrants significant underperform cold style entrants,

especially for funds adopting investment styles tilted towards small-cap and growth strategies. Table 1.20 repeats the comparison of hot and cold style entrants using buy-and-hold portfolio approach, and show similar results as Table 1.5.

1.5.5.2 One-Dimensional Styles

Table 1.21 reports the results of two-sample t-tests by categorizing entrant fund styles using only one of the two style dimensions at one time. The results are consistent with those reported in Table 1.2 and further show that underperformance of hot style entrant funds is most prominent in growth, blend, small-cap, and mid-cap styles.

1.5.6 Alternative Measures for Performance on Buy-and-Hold Portfolios of Entrant Funds

When comparing the performance on buy-and-hold portfolios of hot and cold style entrant funds in the main results section, I use Carhart 4-factor alpha to account for return components attributed to exposure to well-known risk factors (Carhart, 1997) as much as possible. Table 1.22 and Table 1.23 show that using CAPM alpha or the Fama-French 3-factor alpha as alternative performance measures yield findings consistent with those using Carhart 4-factor alpha. The performance difference between equally weighted hot and cold portfolios of entrant funds is -5 basis points per month measured by CAPM alpha, and -7 basis points per month in 3-factor alpha, compared to -5 basis points per month in 4-factor alpha reported in Table 1.5. For value-weighted portfolios, the estimated performance differences are both -11 basis points per month using CAPM alpha and 3-factor alpha, the same as that using 4-factor alpha. The statistical significance of the differences in performance is also similar to that of the

estimates using Carhart 4-factor model. In both cases, the performance differences are statistically more significant for value-weighted portfolios, suggesting that entrant underperformance is more prominent for hot style funds that grow larger. For Fama-French 3-factor model, the signs of the factor loadings on HML and SMB also suggest that hot entrants tend to tilt their holdings more heavily towards growth and small stocks.

1.6 Extension

In this section, I explore alternative notions of fund investment styles and the relation between entrant fund performance and past style performance. Although intuitive and widely adopted in practice, using size and book-to-market characteristics to categorize mutual funds is not the only way to think about fund styles. I consider two other salient features of stock holdings that may be used to define fund styles: industry and dividend. The additional empirical findings below may serve as external validity exercises for the thesis of this chapter, and shed more light on the relation between entrant fund performance and style performance.

1.6.1 Industry Concentrated Funds and Hot v Cold Industries

Aside from stock characteristics, another attribute investors often use to categorize stocks is the industry that a company belongs to. Similarly, investors may categorize mutual funds using the industries if when their portfolio holdings are heavily concentrated in certain industries. In the context of this chapter, industry could be considered by investors as the investment style of mutual funds, especially for funds with industry

concentrated portfolios. Then, by extrapolating the earlier argument in this chapter, one might wonder whether entrant fund performance could be related to past industry performance.

To explore this question, I examine a subsample of the 2,801 entrant funds in the main sample that are industry concentrated. To define industries, I follow Kacperczyk, Sialm, and Zheng (2005) to create ten industry classifications by combining similar groups in the 48 industry classifications used by Fama and French (1997). Table 1.24 shows the average weight of the ten industries in the total market portfolio over the sample period of 1991–2015, as well as the average industry weight in the initial portfolios of the 2,801 entrant funds in the sample. On average, the industry composition of the portfolios of entrant funds is quite similar to that of the market portfolio. I define an entrant fund to be concentrated in an industry if the industry weight in its initial portfolio is more than three times of the industry weight in the market portfolio at the time of its entry and is at least 20%, or if the industry weight in its initial portfolio is more than 50%. As a result, I find 474 incidences of entrant funds concentrated in certain industries and 437 distinct industry concentrated entrant funds.

For these 474 observations, I group them into hot and cold industry entrants based on the hotness of the industry they concentrate in. I consider an industry to be hot if the CAPM alpha of the value-weighted portfolio of all stocks in that industry in the past 24 months is above the time-series median in the sample period. Table 1.25 shows the comparison of 36-month post-entry fund performance of hot and cold industry entrants. Overall, there are more hot industry entrants than cold industry entrants. Some industries have more prominent presence in this sample than others. The most

represented industries are business equipment and services, consumer non-durables, and wholesale and retail. In contrast, there are few funds in the sample that are concentrated in consumer durables, finance, and healthcare. For most industries, hot entrants on average perform worse than cold entrants. For example, seven out of the ten industry classification show negative differences in Carhart 4-factor alpha. The differences are most significant for business equipment and services, finance, consumer non-durables, and wholesale and retail. One reason for the differences in significance across industries could be the number of observations in the sample. Another reason could be that investors are more prone to extrapolative beliefs when considering stocks in certain industries. Overall, the hot entrants underperform cold entrants by 0.23% per month in terms of 4-factor alpha in the 36 months following entries. Regressions of post-entry performance on hot industry dummy variable estimate that differences in performance are of similar size at around 20 bps per month for various specifications. Those results are reported in Table 1.26.

1.6.2 Funds Investing in High v Low Dividend Yield Stocks

Another interesting aspect of stock characteristics that investors often consider is dividend payout. Baker and Wurgler (2006) and Baker and Wurgler (2007) argue that sentimental investors associate dividend-paying stocks with profitability and consider them as safe investments. In contrast, "no dividend" is associated with traits such as "no earnings" and "young age", and non-dividend-paying stocks are considered as speculative opportunities. If investors with these views are prevalent in the market, mutual funds that invest in high or low dividend yield stocks may be treated as different investment

styles, and the popularity of either of them may be related to the future performance of entrants to the styles.

As an extension to the main findings of this study, I explore the relation between entrant fund performance and style hotness using average dividend yield of stock holdings as an alternative method to categorize fund styles. In the 1991–2015 fund sample, I calculate fund-level dividend yield as the weighted average of 12-month dividend yield of fund holdings. The stock dividend yield is calculated at monthly frequency as the dividend payment in the past 12 months divided by the month-end stock price. Funds with fund-level dividend yield above the cross-sectional median are classified as high dividend yield style. Otherwise, they are classified as low dividend yield style. Similar to the main analyses in Section 1.4.1, I consider a style at a particular time to be hot or cold based on whether the weighted average return of funds in that style category minus the market return in the past 24 months is above or below the time-series sample median.

Table 1.27 displays the comparison between the performance of hot and cold entrant funds using dividend yield style to define fund style categories. Overall, hot entrants underperform cold entrants by 8 to 10 basis points per month on average, depending on the choice of factor-based performance measure. When examining low and high dividend yield style funds separately, I find drastic differences between the two groups. For low dividend yield style entrants, there are 870 hot entrants and 528 cold entrants. This wide difference suggests trend-chasing behavior of fund entry in this style. In contrast, the number of hot and cold entrants among high dividend yield style funds are almost evenly divided, with 699 funds classified as hot entrants and 704

classified as cold entrants. in addition, the underperformance of hot style entrants is found significant only for low dividend yield styles. On average, hot low dividend yield entrants underperforms cold entrants by about 20 basis points per month. For high dividend yield entrants, the performance differences between hot and cold entrants seem to be small and insignificant. The results can be related to the previous findings that hot entrant underperformance in more prominent for funds with growth- and small-stock-oriented styles. It also suggests that there might be certain level of segmentation of clienteles for funds with different styles, and investors in low dividend yield style funds, as well as growth- and small-stock-oriented funds are more prone to extrapolative biases when assessing style performance.

1.7 Conclusion

In this chapter, I study the implications of mutual fund entry decision on performance of new funds. For U.S. active equity funds opened during 1991–2015, I find that the post-entry fund performance is worse for entrants that adopt investment styles that have recently performed well. Entrant funds also underperform incumbent funds in the same style categories more when past style performance is higher. These findings are consistent with investors categorizing funds by investment styles and forming extrapolative beliefs on style performance, which leads to changing distributions of skills of fund entrants in different style categories at different times.

Tables and Figures

Table 1.1: Number of Entrant and Incumbent Funds by Year

Year	#Incumbet	#Entrant	#Entrant	Small			Mid			Large		
			in Sample	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
1980	298											
1981	309											
1982	317	6	4	0	1	1	1	0	0	0	0	1
1983	311	23	16	7	6	0	0	1	2	0	0	0
1984	346	16	13	6	1	0	2	2	1	0	0	1
1985	366	34	24	8	4	3	2	1	3	0	1	2
1986	409	38	19	2	3	3	1	2	2	0	0	6
1987	463	34	20	7	0	0	1	4	0	0	1	7
1988	508	10	3	1	1	0	0	0	0	0	1	0
1989	563	20	11	1	2	1	0	2	0	0	3	2
1990	609	31	16	2	3	0	0	3	1	3	2	2
1991	708	50	43	12	5	6	2	5	3	2	5	3
1992	778	132	87	14	13	6	12	6	4	4	11	17
1993	965	154	110	35	7	8	10	12	7	3	13	15
1994	1,156	154	116	31	8	10	9	12	8	7	10	21
1995	1,341	142	104	29	6	14	11	3	10	2	15	14
1996	1,412	187	139	37	10	13	15	24	7	2	14	17
1997	1,595	148	116	23	11	15	5	11	9	5	20	17
1998	1,710	184	179	33	16	22	19	16	15	9	25	24
1999	1,866	181	169	32	14	8	23	22	14	8	30	18

(*continued*)

Year	#Incumbet	#Entrant	#Entrant in Sample	Small			Mid			Large		
				Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
2000	2,034	228	218	43	13	18	37	21	23	13	32	18
2001	2,202	164	143	19	13	20	10	15	23	11	21	11
2002	2,328	111	102	14	14	18	8	7	13	2	13	13
2003	2,383	119	112	14	10	19	16	6	16	4	14	13
2004	2,390	107	98	22	8	14	12	12	9	3	7	11
2005	2,407	175	159	35	16	16	19	9	23	1	13	27
2006	2,352	134	126	25	16	16	16	11	10	1	12	19
2007	2,480	136	114	21	10	8	18	15	10	5	8	19
2008	2,680	73	60	17	7	3	13	3	5	1	4	7
2009	2,627	68	63	11	4	4	5	7	5	8	8	11
2010	2,950	105	86	22	12	6	9	12	2	7	4	12
2011	2,920	102	94	9	13	16	8	8	8	6	11	15
2012	2,863	104	99	15	10	1	16	13	9	3	11	21
2013	2,833	109	107	30	16	9	14	13	11	1	5	8
2014	2,761	90	82	21	17	5	9	9	8	0	4	9
2015	2,760	84	75	8	21	4	7	9	9	3	4	10
2016	2,737											
2017	2,614											
2018	2,489											
1982–2015		3,453	2,927									
1991–2015		3,241	2,801									

Table 1.2: Comparing Post-Entry Performance of Hot and Cold Style Entrant Funds

An investment style is considered as in hot status if the TNA-weighted average returns of funds in the style category minus the value-weighted CRSP index return in the previous 24 months is above the time-series median of the entire sample. An entrant fund is considered as a hot style entrant fund if its initial holding-based style at the time of its entry is in hot status. Post-entry performance is measured over the 36-month window after the month of the funds' inception date. If the fund is closed within the 36 months, it is still included in the calculation. Return in excess of MKT is measured as the average fund monthly return over the value-weighted CRSP index return. *t*-statistics of two sample mean tests are reported for the difference between average performance of hot and cold style entrant funds. The sample period is 1991–2015.

		Small			Mid			Large		
	All	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
Panel A: Number of Entrants										
Hot	1,463	354	152	166	159	141	150	57	108	176
Cold	1,338	218	138	113	164	140	111	54	206	194
Total	2,801	572	290	279	323	281	261	111	314	370
Panel B: Return in Excess of MKT										
Hot	-0.035	0.025	0.096	0.119	-0.129	-0.103	0.045	-0.292	-0.201	-0.157
Cold	0.002	0.288	0.048	-0.005	-0.050	0.064	0.036	-0.094	-0.151	-0.177
Difference	-0.037	-0.264	0.048	0.124	-0.079	-0.020	0.010	-0.198	-0.050	0.020
t-stat	-1.458	-3.698	0.553	1.171	-1.248	-2.282	0.133	-2.048	-0.856	0.406

(continued)

	All	Small			Mid			Large		
		Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
Panel C: CAPM Alpha										
Hot	-0.043	-0.012	0.024	0.038	-0.145	-0.073	0.052	-0.233	-0.127	-0.090
Cold	0.038	0.330	0.037	0.069	-0.019	0.108	0.044	-0.099	-0.097	-0.134
Difference	-0.080	-0.342	-0.013	-0.031	-0.125	-0.181	0.008	-0.134	-0.030	0.044
t-stat	-3.363	-4.679	-0.159	-0.324	-2.110	-2.648	0.123	-1.743	-0.636	1.116
Panel D: Fama-French 3-Factor Alpha										
Hot	-0.048	0.054	-0.043	-0.056	-0.081	-0.114	-0.082	-0.127	-0.057	-0.107
Cold	0.007	0.277	-0.006	-0.061	-0.021	0.093	-0.038	-0.040	-0.076	-0.157
Difference	-0.055	-0.223	-0.037	0.005	-0.061	-0.207	-0.044	-0.087	0.020	0.050
t-stat	-2.638	-3.305	-0.569	0.075	-1.016	-3.498	-0.798	-1.305	0.458	1.411
Panel E: Carhart 4-Factor Alpha										
Hot	-0.060	0.002	-0.048	-0.046	-0.092	-0.113	-0.074	-0.109	-0.070	-0.101
Cold	0.001	0.211	-0.007	-0.014	-0.045	0.058	0.015	-0.075	-0.082	-0.123
Difference	-0.061	-0.209	-0.041	-0.032	-0.046	-0.171	-0.089	-0.035	0.012	0.022
t-stat	-3.118	-3.360	-0.654	-0.479	-0.856	-3.083	-1.743	-0.530	0.293	0.738

Table 1.3: Regressions of Post-Entry Fund Performance on Hot Style Dummy Variable

This table reports results of regressions of fund performance in the m months immediately following its entry on a dummy variable that equals one if the entrant fund belongs to a hot style category at the time of entry. The dependent variables are measured by return in excess of the value-weighted CRSP index return, the CAPM alpha, the Fama-French 3-factor alpha, and the Carhart 4-factor alpha. Each fund entry during the period of 1991–2015 contributes to one observation in the regressions reported here. Fund style fixed effects are included in all specifications. The t-statistics reported are calculated using standard errors clustered at style-year level.

m	Coef.	t-stat	N	Adj. Rsq.
Panel A: Return in Excess of MKT				
12	-0.058	-0.53	2,801	0.020
24	-0.047	-0.58	2,801	0.022
36	-0.071	-1.13	2,801	0.029
60	-0.107	-2.34	2,801	0.042
Panel B: CAPM Alpha				
12	-0.103	-0.96	2,801	0.016
24	-0.097	-1.18	2,801	0.019
36	-0.108	-1.70	2,801	0.024
60	-0.143	-3.08	2,801	0.038
Panel C: Fama-French 3-Factor Alpha				
12	-0.109	-1.53	2,801	0.014
24	-0.069	-1.34	2,801	0.024
36	-0.075	-1.88	2,801	0.026
60	-0.041	-1.50	2,801	0.016
Panel D: Carhart 4-Factor Alpha				
12	-0.109	-1.56	2,801	0.016
24	-0.075	-1.51	2,801	0.021
36	-0.078	-2.18	2,801	0.018
60	-0.045	-1.89	2,801	0.008

Table 1.4: Regressions of Post-Entry Fund Performance on Past Style Performance

This table reports results of regressions of fund performance in the m months immediately following its entry on past style performance. The dependent variables are measured by return in excess of the value-weighted CRSP index return, the CAPM alpha, the Fama-French 3-factor alpha, and the Carhart 4-factor alpha. Past style performance is measured by the value-weighted average return of all incumbent funds in the same style category in excess of the value-weighted CRSP index return in the past 24 months. Each fund entry during the period of 1991–2015 contributes to one observation in the regressions reported here. Fund style fixed effects are included in all specifications. The t-statistics reported are calculated with standard errors clustered at style-year level.

m	Coef.	t-stat	N	Adj. Rsq.
Panel A: Return in Excess of MKT				
12	-0.170	-0.86	2,801	0.023
24	-0.216	-1.35	2,801	0.033
36	-0.202	-1.55	2,801	0.042
60	-0.204	-2.28	2,801	0.058
Panel B: CAPM Alpha				
12	-0.205	-1.05	2,801	0.020
24	-0.263	-1.69	2,801	0.035
36	-0.246	-1.87	2,801	0.044
60	-0.254	-2.87	2,801	0.062
Panel C: Fama-French 3-Factor Alpha				
12	-0.304	-2.84	2,801	0.028
24	-0.260	-3.44	2,801	0.049
36	-0.209	-3.33	2,801	0.047
60	-0.108	-2.64	2,801	0.024
Panel D: Carhart 4-Factor Alpha				
12	-0.283	-2.73	2,801	0.027
24	-0.262	-3.56	2,801	0.047
36	-0.199	-3.56	2,801	0.038
60	-0.105	-3.02	2,801	0.016

Table 1.5: Comparison of Returns on Buy-and-Hold Portfolios of Hot and Cold Style Entrant Funds

This table reports results of time-series regressions of monthly returns of buy-and-hold portfolios of entrant funds on Carhart 4-factors. For the sample period between 1991 and 2018, each entrant fund is added to the hot or non-hot fund portfolio and held for 5 years. Equally weighted portfolios are rebalanced at the end of every year. For individual portfolios, the following time-series regression is estimated:

$$R_{p,t} - R_{f,t} = a + b \cdot RMRF_t + h \cdot HML_t + s \cdot SMB_t + u \cdot UMD_t + e_t.$$

To estimate the difference in performance between hot and non-hot portfolios, the difference in returns of the two portfolios is used as the dependent variable. t-statistics of coefficient estimates are in parentheses. Each regression uses 336 monthly observations.

	Coefficient Estimates					
	a	b	h	s	u	Adj. Rsq.
Panel A: Equally Weighted Portfolio Returns						
Hot	-0.10	1.00	-0.01	0.27	0.01	0.98
	(-2.75)	(110.02)	(-0.89)	(23.16)	(0.68)	
Cold	-0.05	0.95	0.05	0.20	0.01	0.98
	(-1.59)	(122.20)	(4.39)	(20.47)	(1.47)	
Difference	-0.05	0.05	-0.06	0.07	0.00	0.36
	(-1.63)	(6.46)	(-5.47)	(6.65)	(-0.68)	
Panel B: Value Weighted Portfolio Returns						
Hot	-0.18	1.01	-0.05	0.25	0.03	0.97
	(-3.72)	(84.47)	(-2.80)	(16.56)	(2.81)	
Cold	-0.07	0.98	-0.03	0.15	0.03	0.98
	(-2.06)	(111.53)	(-2.22)	(13.70)	(4.20)	
Difference	-0.11	0.03	-0.02	0.10	0.00	0.15
	(-2.12)	(2.18)	(-1.12)	(6.22)	(-0.28)	

Table 1.6: Regressions of Post-Entry Fund Performance Relative to Peers on Hot Style Dummy Variable

This table reports results of regressions of fund performance relative to peers in the m months immediately following its entry on a dummy variable that equals one if the entrant fund belongs to a hot style category at the time of entry. The dependent variables are measured by differences in return in excess of the value-weighted CRSP index return, the CAPM alpha, the Fama-French 3-factor alpha, and the Carhart 4-factor alpha between the entrant fund and the value-weighted average of incumbent funds in the same style category. Each fund entry during the period of 1991–2015 contributes to one observation in the regressions reported here. Fund style fixed effects are included in all specifications. The t-statistics reported are calculated using standard errors clustered at style-year level.

m	Coef.	t-stat	N	Adj. Rsq.
Panel A: Return in Excess of MKT				
12	-0.108	-1.74	2,801	0.014
24	-0.088	-1.94	2,801	0.017
36	-0.086	-2.17	2,801	0.021
60	-0.046	-1.46	2,801	0.023
Panel B: CAPM Alpha				
12	-0.087	-1.53	2,801	0.020
24	-0.091	-2.08	2,801	0.027
36	-0.091	-2.37	2,801	0.031
60	-0.062	-2.03	2,801	0.029
Panel C: Fama-French 3-Factor Alpha				
12	-0.131	-2.20	2,801	0.019
24	-0.099	-2.27	2,801	0.026
36	-0.112	-3.08	2,801	0.030
60	-0.073	-2.56	2,801	0.026
Panel D: Carhart 4-Factor Alpha				
12	-0.116	-2.01	2,801	0.021
24	-0.106	-2.43	2,801	0.029
36	-0.104	-2.94	2,801	0.032
60	-0.077	-2.73	2,801	0.025

Table 1.7: Regressions of Post-Entry Fund Performance Relative to Peers on Past Style Performance

This table reports results of regressions of fund performance relative to peers in the m months immediately following its entry on past style performance. The dependent variables are measured by differences in return in excess of the value-weighted CRSP index return, the CAPM alpha, the Fama-French 3-factor alpha, and the Carhart 4-factor alpha between the entrant fund and the value-weighted average of incumbent funds in the same style category. Past style performance is measured by the value-weighted average return of all incumbent funds in the same style category in excess of the value-weighted CRSP index return in the past 24 months. Each fund entry during the period of 1991–2015 contributes to one observation in the regressions reported here. Fund style fixed effects are included in all specifications. The t-statistics reported are calculated using standard errors clustered at style-year level.

m	Coef.	t-stat	N	Adj. Rsq.
Panel A: Return in Excess of MKT				
12	-0.156	-1.69	2,801	0.015
24	-0.164	-2.56	2,801	0.022
36	-0.146	-2.20	2,801	0.026
60	-0.096	-1.93	2,801	0.028
Panel B: CAPM Alpha				
12	-0.122	-1.41	2,801	0.021
24	-0.169	-2.80	2,801	0.033
36	-0.153	-2.48	2,801	0.038
60	-0.117	-2.54	2,801	0.036
Panel C: Fama-French 3-Factor Alpha				
12	-0.217	-2.44	2,801	0.024
24	-0.212	-3.84	2,801	0.040
36	-0.203	-4.02	2,801	0.044
60	-0.143	-3.71	2,801	0.038
Panel D: Carhart 4-Factor Alpha				
12	-0.191	-2.15	2,801	0.024
24	-0.230	-3.92	2,801	0.046
36	-0.198	-3.88	2,801	0.047
60	-0.147	-3.78	2,801	0.038

Table 1.8: Length of Fund Incubation Period (1996–2006)

This table reports the distribution of the number of months between fund inception date and fund ticker creation date for entrant funds in the sample period 1996–2006. Fund inception date is the earliest *first_offer_dt* in the CRSP database for all fund share classes of a fund. Fund ticker creation date is the earliest date any of the share classes of a fund created a ticker symbol with NASD.

N	≤ 1	$(1, 12]$	$(12, 24]$	> 24
1,293	669	396	147	81

Table 1.9: Comparing Post-Entry Performance of Hot and Cold Style Entrant Funds (1996–2006)

This table compares post-entry performance of hot and cold style entrant funds for the period of 1996–2006. Fund entry dates are determined using the fund inception dates. Post-entry performance is measured over the 36-month window following the fund entry date.

		Small			Mid			Large		
	All	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
Panel A: Number of Entrants										
Hot	617	139	68	88	60	51	84	21	51	55
Cold	676	114	46	57	92	81	46	30	115	95
Total	1,293	253	114	145	152	132	130	51	166	150
Panel B: CAPM Alpha										
Hot	0.035	0.079	0.217	0.184	-0.138	-0.033	0.115	-0.360	-0.150	-0.090
Cold	0.185	0.708	0.427	0.214	0.114	0.271	0.190	-0.142	-0.109	-0.127
Difference	-0.150	-0.628	-0.210	-0.030	-0.253	-0.304	-0.075	-0.218	-0.041	0.037
t-stat	-3.644	-5.062	-1.470	-0.202	-2.627	-2.675	-0.759	-1.792	-0.521	0.449
Panel C: Fama-French 3-Factor Alpha										
Hot	-0.057	-0.028	-0.015	-0.033	-0.088	-0.129	-0.073	-0.187	-0.008	-0.088
Cold	0.102	0.541	0.183	-0.074	0.075	0.219	0.045	-0.073	-0.061	-0.149
Difference	-0.159	-0.569	-0.198	0.041	-0.163	-0.348	-0.118	-0.115	0.053	0.060
t-stat	-4.444	-4.998	-1.645	0.406	-1.583	-3.267	-1.366	-1.085	0.753	0.780
Panel D: Carhart 4-Factor Alpha										
Hot	-0.054	-0.044	-0.019	-0.032	-0.071	-0.128	-0.053	-0.170	-0.017	-0.065
Cold	0.093	0.456	0.211	0.002	0.029	0.163	0.114	-0.070	-0.066	-0.112
Difference	-0.147	-0.500	-0.230	-0.034	-0.100	-0.291	-0.167	-0.100	0.048	0.046
t-stat	-4.508	-4.831	-2.027	-0.332	-1.085	-2.968	-2.116	-1.084	0.737	0.774

Table 1.10: Robustness to Fund Incubation: Comparing Post-Entry Performance of Hot and Cold Style Entrant Funds (1996–2006)

This table compares post-entry performance of hot and cold style entrant funds for the period of 1996–2006. Fund entry dates are determined using the fund ticker creation dates, which exclude fund incubation periods. Post-entry performance is measured over the 36-month window following the fund entry date.

		Small			Mid			Large		
	All	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
Panel A: Number of Entrants										
Hot	690	163	79	98	60	57	98	19	54	62
Cold	603	90	35	47	92	75	32	32	112	88
Total	1,293	253	114	145	152	132	130	49	157	150
Panel B: CAPM Alpha										
Hot	0.028	0.045	0.264	0.136	-0.077	-0.014	0.109	-0.371	-0.196	-0.164
Cold	0.141	0.713	0.638	0.313	0.149	0.158	-0.058	-0.289	-0.155	-0.154
Difference	-0.113	-0.668	-0.374	-0.177	-0.226	-0.172	0.167	-0.082	-0.042	-0.010
t-stat	-2.795	-5.273	-2.536	-1.166	-2.411	-1.532	1.517	-0.617	-0.624	-0.136
Panel C: Fama-French 3-Factor Alpha										
Hot	-0.094	-0.091	-0.016	-0.085	-0.068	-0.186	-0.098	-0.203	-0.037	-0.160
Cold	0.035	0.356	0.284	-0.084	0.072	0.149	-0.091	-0.200	-0.092	-0.170
Difference	-0.129	-0.447	-0.300	-0.001	-0.140	-0.334	-0.007	-0.003	0.055	0.010
t-stat	-3.999	-4.218	-2.612	-0.010	-1.538	-3.196	-0.086	-0.026	0.977	0.165
Panel D: Carhart 4-Factor Alpha										
Hot	-0.092	-0.106	-0.033	-0.088	-0.054	-0.176	-0.084	-0.169	-0.023	-0.140
Cold	0.032	0.316	0.297	-0.008	0.009	0.090	0.029	-0.200	-0.094	-0.125
Difference	-0.123	-0.422	-0.330	-0.080	-0.064	-0.265	-0.113	0.031	0.071	-0.015
t-stat	-4.139	-4.279	-3.104	-0.822	-0.775	-2.958	-1.358	0.255	1.314	-0.264

Table 1.11: Robustness to Fund Incubation: Regressions of Post-Entry Fund Performance on Hot Style Dummy Variable (1996–2006)

This table compares results of regressions of fund performance on hot style dummy variable for alternative definitions of fund entry date. The left panel reports results using fund inception date as fund entry date, and the right panel uses fund ticker creation date and excludes fund incubation period. The dependent variables are fund performance in the m months following fund entry measured by the CAPM alpha, the Fama-French 3-factor alpha, and the Carhart 4-factor alpha. The independent variable is a dummy variable that equals to one if the entrant fund is a hot style entrant. Each fund entry during the period of 1996–2006 contributes to one observation in each regression. Fund style fixed effects are included in all specifications. The t-statistics reported are calculated using standard errors clustered at style-year level.

	Baseline				Excluding Fund Incubation Returns			
m	Coef.	t	N	Adj. Rsq.	Coef.	t	N	Adj. Rsq.
Panel A: CAPM Alpha								
12	-0.235	-1.29	1,293	0.031	-0.242	-1.89	1,293	0.029
24	-0.207	-1.58	1,293	0.039	-0.190	-1.92	1,293	0.043
36	-0.230	-2.63	1,293	0.080	-0.226	-3.01	1,293	0.088
60	-0.245	-4.83	1,293	0.168	-0.214	-4.47	1,293	0.138
Panel B: Fama-French 3-Factor Alpha								
12	-0.255	-2.12	1,293	0.018	-0.239	-2.59	1,293	0.010
24	-0.191	-2.46	1,293	0.036	-0.177	-2.51	1,293	0.028
36	-0.188	-3.34	1,293	0.046	-0.161	-3.05	1,293	0.033
60	-0.107	-2.66	1,293	0.030	-0.075	-2.15	1,293	0.015
Panel C: Carhart 4-Factor Alpha								
12	-0.233	-2.05	1,293	0.023	-0.196	-2.23	1,293	0.010
24	-0.195	-2.61	1,293	0.038	-0.167	-2.52	1,293	0.026
36	-0.179	-3.51	1,293	0.040	-0.159	-3.31	1,293	0.029
60	-0.105	-2.96	1,293	0.023	-0.071	-2.36	1,293	0.010

Table 1.12: Robustness to Excluding Fund Returns in the First Year: Comparing Post-Entry Performance of Hot and Cold Style Entrant Funds

An investment style is considered as in hot status if the TNA-weighted average returns of funds in the style category minus the value-weighted CRSP index return in the previous 24 months is above the time-series median of the entire sample. An entrant fund is considered as a hot style entrant fund if its initial holding-based style at the time of its entry is in hot status. Post-entry performance is measured over the 36-month window starting from one year after funds' inception date. If the fund is closed within the 36 months, it is still included in the calculation. Return in excess of MKT is measured as the average fund monthly return over the value-weighted CRSP index return. t-statistics of two sample mean tests are reported for the difference between average performance of hot and cold style entrant funds. The sample period is 1991–2015.

		Small			Mid			Large		
	All	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
Panel A: Number of Entrants										
Hot	1,463	354	152	166	159	141	150	57	108	176
Cold	1,338	218	138	113	164	140	111	54	206	194
Total	2,801	572	290	279	323	281	261	111	314	370
Panel B: Return in Excess of MKT										
Hot	-0.042	0.011	0.075	0.115	-0.126	-0.106	0.048	-0.309	-0.209	-0.163
Cold	-0.002	0.252	0.090	-0.016	-0.052	0.059	0.035	-0.096	-0.146	-0.191
Difference	-0.040	-0.241	-0.015	0.131	-0.073	-0.164	0.012	-0.213	-0.063	0.028
t-stat	-1.555	-3.407	-0.170	1.258	-1.146	-2.161	0.164	-2.281	-1.038	0.583

(continued)

	All	Small			Mid			Large		
		Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
Panel C: CAPM Alpha										
Hot	-0.055	-0.032	0.006	0.028	-0.150	-0.078	0.049	-0.259	-0.142	-0.093
Cold	0.034	0.302	0.077	0.056	-0.020	0.097	0.057	-0.100	-0.094	-0.147
Difference	-0.089	-0.334	-0.071	-0.028	-0.130	-0.176	-0.008	-0.159	-0.048	0.054
t-stat	-3.742	-4.640	-0.902	-0.295	-2.171	-2.533	-0.127	-2.072	-1.012	1.386
Panel D: Fama-French 3-Factor Alpha										
Hot	-0.060	0.026	-0.051	-0.050	-0.093	-0.120	-0.089	-0.149	-0.072	-0.113
Cold	0.001	0.244	0.008	-0.065	-0.013	0.077	-0.039	-0.047	-0.074	-0.164
Difference	-0.061	-0.218	-0.059	0.015	-0.080	-0.198	-0.050	-0.102	0.002	0.050
t-stat	-2.970	-3.301	-0.911	0.223	-1.353	-3.335	-0.879	-1.445	0.055	1.478
Panel E: Carhart 4-Factor Alpha										
Hot	-0.074	-0.027	-0.058	-0.047	-0.104	-0.120	-0.085	-0.139	-0.084	-0.105
Cold	-0.003	0.192	0.005	-0.015	-0.043	0.043	0.015	-0.083	-0.079	-0.127
Difference	-0.071	-0.219	-0.062	-0.032	-0.061	-0.163	-0.100	-0.056	-0.005	0.022
t-stat	-3.686	-3.584	-1.011	-0.479	-1.141	-2.971	-1.911	-0.804	-0.138	0.734

Table 1.13: Robustness to Excluding Fund Returns in the First Year: Regressions of Post-Entry Fund Performance on Hot Style Dummy Variable

This table reports results of regressions of fund performance in the m months starting from one year after its entry on a dummy variable that equals one if the entrant fund belongs to a hot style category at the time of entry. The dependent variables are measured by differences in return in excess of the value-weighted CRSP index return, the CAPM alpha, the Fama-French 3-factor alpha, and the Carhart 4-factor alpha between the entrant fund and the value-weighted average of incumbent funds in the same style category. Each fund entry during the period of 1991–2015 contributes to one observation in each regression. Fund style fixed effects are included in all specifications. The t-statistics reported are calculated using standard errors clustered at style-year level.

m	Coef.	t-stat	N	Adj. Rsq.
Panel A: Return in Excess of MKT				
12	-0.035	-0.35	2,801	0.017
24	-0.041	-0.52	2,801	0.021
36	-0.072	-1.15	2,801	0.028
60	-0.108	-2.41	2,801	0.043
Panel B: CAPM Alpha				
12	-0.115	-1.14	2,801	0.015
24	-0.097	-1.23	2,801	0.017
36	-0.115	-1.83	2,801	0.024
60	-0.147	-3.20	2,801	0.040
Panel C: Fama-French 3-Factor Alpha				
12	-0.104	-1.59	2,801	0.011
24	-0.080	-1.62	2,801	0.022
36	-0.080	-2.01	2,801	0.023
60	-0.043	-1.59	2,801	0.014
Panel D: Carhart 4-Factor Alpha				
12	-0.117	-1.75	2,801	0.014
24	-0.087	-1.81	2,801	0.019
36	-0.087	-2.42	2,801	0.016
60	-0.048	-2.02	2,801	0.007

Table 1.14: Robustness to Look-Ahead Bias: Comparing Post-Entry Performance of Hot and Cold Style Entrant Funds

An investment style is considered as in hot status if the TNA-weighted average returns of funds in the style category minus the value-weighted CRSP index return in the previous 24 months is above the cumulative median for the sample up to the time of the observation. An entrant fund is considered as a hot style entrant fund if its initial holding-based style at the time of its entry is in hot status. Post-entry performance is measured over the 36-month window starting the month end of funds' inception date. If the fund is closed within the 36 months, it is still included in the calculation. Return in excess of MKT is measured as the average fund monthly return over the value-weighted CRSP index return. t-statistics of two sample mean tests are reported for the difference between average performance of hot and cold style entrant funds. The sample period is 1991–2015.

		Small			Mid			Large		
	All	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
					Panel A: Number of Entrants					
Hot	1,414	376	149	159	133	132	143	63	130	129
Cold	1,387	196	141	120	190	149	118	48	184	241
Total	2,801	572	290	279	323	281	261	111	314	370
					Panel B: Return in Excess of MKT					
Hot	-0.023	0.024	0.112	0.152	-0.139	-0.083	0.063	-0.264	-0.185	-0.167
Cold	-0.011	0.319	0.032	-0.042	-0.054	0.035	0.015	-0.106	-0.157	-0.168
Difference	-0.012	-0.295	0.080	0.195	-0.085	-0.118	0.048	-0.159	-0.028	0.000
t-stat	-0.462	-4.056	0.935	1.867	-1.321	-1.606	0.654	-1.621	-0.489	0.006

(continued)

	All	Small			Mid			Large		
		Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
Panel C: CAPM Alpha										
Hot	-0.027	-0.002	0.045	0.071	-0.131	-0.056	0.070	-0.199	-0.117	-0.097
Cold	0.018	0.349	0.014	0.023	-0.046	0.082	0.023	-0.126	-0.100	-0.122
Difference	-0.045	-0.351	0.031	0.048	-0.084	-0.138	0.048	-0.073	-0.017	0.024
t-stat	-1.882	-4.687	0.393	0.502	-1.392	-1.994	0.750	-0.937	-0.379	0.591
Panel D: Fama-French 3-Factor Alpha										
Hot	-0.063	-0.049	-0.044	-0.061	-0.107	-0.111	-0.083	-0.111	-0.056	-0.118
Cold	0.011	0.006	-0.007	-0.053	-0.011	0.078	-0.039	-0.051	-0.079	-0.142
Difference	-0.074	-0.055	-0.037	-0.008	-0.096	-0.189	-0.044	-0.061	0.023	0.024
t-stat	-3.526	-2.621	-0.568	-0.122	-1.590	-3.181	-0.815	-0.899	0.567	0.645
Panel E: Carhart 4-Factor Alpha										
Hot	-0.060	-0.004	-0.047	-0.055	-0.103	-0.113	-0.075	-0.096	-0.063	-0.110
Cold	-0.001	0.246	-0.010	-0.005	-0.044	0.048	0.012	-0.088	-0.088	-0.114
Difference	-0.059	-0.249	-0.037	-0.049	-0.058	-0.161	-0.086	-0.007	0.025	0.004
t-stat	-3.031	-3.936	-0.590	-0.743	-1.065	-2.893	-1.712	-0.112	0.643	0.134

Table 1.15: Robustness to Look-Ahead Bias: Regressions of Post-Entry Fund Performance on Hot Style Dummy Variable

This table reports results of regressions of fund performance in the m months following its entry on a dummy variable that equals one if the entrant fund belongs to a hot style category at the time of entry. The dependent variables are measured by differences in return in excess of the value-weighted CRSP index return, the CAPM alpha, the Fama-French 3-factor alpha, and the Carhart 4-factor alpha between the entrant fund and the value-weighted average of incumbent funds in the same style category. Each fund entry during the period of 1991–2015 contributes to one observation in each regression. Fund style fixed effects are included in all specifications. The t-statistics reported are calculated using standard errors clustered at style-year level.

m	Coef.	t-stat	N	Adj. Rsq.
Panel A: Return in Excess of MKT				
12	-0.018	-0.15	2,801	0.019
24	-0.018	-0.21	2,801	0.022
36	-0.055	-0.84	2,801	0.028
60	-0.097	-2.00	2,801	0.040
Panel B: CAPM Alpha				
12	-0.046	-0.41	2,801	0.014
24	-0.063	-0.73	2,801	0.017
36	-0.081	-1.20	2,801	0.021
60	-0.124	-2.54	2,801	0.033
Panel C: Fama-French 3-Factor Alpha				
12	-0.120	-1.61	2,801	0.015
24	-0.088	-1.66	2,801	0.026
36	-0.089	-2.11	2,801	0.028
60	-0.058	-1.99	2,801	0.018
Panel D: Carhart 4-Factor Alpha				
12	-0.097	-1.35	2,801	0.015
24	-0.088	-1.71	2,801	0.022
36	-0.086	-2.31	2,801	0.019
60	-0.056	-2.23	2,801	0.009

Table 1.16: Measuring Style Performance Using CAPM Alpha: Comparing Post-Entry Performance of Hot and Cold Style Entrant Funds

An investment style is considered as in hot status if the CAPM alpha of TNA-weighted average returns of funds in the style category in the previous 24 months is above the time-series median for the entire sample. An entrant fund is considered as a hot style entrant fund if its initial holding-based style at the time of its entry is in hot status. Post-entry performance is measured over the 36-month window starting the month end of funds' inception date. If the fund is closed within the 36 months, it is still included in the calculation. Return in excess of MKT is measured as the average fund monthly return over the value-weighted CRSP index return. t-statistics of two sample mean tests are reported for the difference between average performance of hot and cold style entrant funds. The sample period is 1991–2015.

		Small			Mid			Large		
	All	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
Panel A: Number of Entrants										
Hot	1,464	340	140	180	155	135	154	55	121	184
Cold	1,337	232	150	99	168	146	107	56	193	186
Total	2,801	572	290	279	323	281	261	111	314	370
Panel B: Return in Excess of MKT										
Hot	-0.050	0.048	0.114	0.091	-0.169	-0.101	-0.024	-0.267	-0.207	-0.211
Cold	0.019	0.237	0.035	0.028	-0.016	0.054	0.135	-0.126	-0.144	-0.125
Difference	-0.069	-0.189	0.079	0.062	-0.153	-0.155	-0.160	-0.141	-0.063	-0.087
t-stat	-2.683	-2.667	0.920	0.575	-2.443	-2.113	-2.153	-1.447	-1.097	-1.808

(continued)

		Small			Mid			Large		
	All	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
Panel C: CAPM Alpha										
Hot	-0.045	0.019	0.038	0.033	-0.148	-0.062	-0.004	-0.206	-0.127	-0.133
Cold	0.040	0.263	0.022	0.082	-0.020	0.091	0.124	-0.129	-0.095	-0.093
Difference	-0.084	-0.244	0.016	-0.049	-0.128	-0.153	-0.128	-0.077	-0.032	-0.040
t-stat	-3.518	-3.347	0.203	-0.500	-2.148	-2.229	-2.001	-0.995	-0.708	-1.009
Panel D: Fama-French 3-Factor Alpha										
Hot	-0.068	0.033	-0.048	-0.075	-0.111	-0.123	-0.119	-0.107	-0.063	-0.139
Cold	0.029	0.294	-0.005	-0.027	0.005	0.092	0.017	-0.064	-0.074	-0.127
Difference	-0.098	-0.260	-0.044	-0.048	-0.116	-0.215	-0.136	-0.043	0.011	-0.012
t-stat	-4.677	-3.916	-0.669	-0.706	-1.947	-3.636	-2.494	-0.644	0.270	-0.329
Panel E: Carhart 4-Factor Alpha										
Hot	-0.069	-0.013	-0.048	-0.050	-0.114	-0.116	-0.096	-0.094	-0.066	-0.109
Cold	0.011	0.221	-0.011	-0.003	-0.026	0.054	0.050	-0.091	-0.085	-0.115
Difference	-0.081	-0.234	-0.036	-0.047	-0.089	-0.170	-0.146	-0.003	0.019	0.006
t-stat	-4.171	-3.823	-0.578	-0.678	-1.646	-3.064	-2.879	-0.045	0.477	0.189

Table 1.17: Measuring Style Performance Using CAPM Alpha: Regressions of Post-Entry Fund Performance on Hot Style Dummy Variable

This table reports results of regressions of fund performance in the m months following its entry on on a dummy variable that equals one if the entrant fund belongs to a hot style category at the time of entry. The dependent variables are measured by differences in return in excess of the value-weighted CRSP index return, the CAPM alpha, the Fama-French 3-factor alpha, and the Carhart 4-factor alpha between the entrant fund and the value-weighted average of incumbent funds in the same style category. Each fund entry during the period of 1991–2015 contributes to one observation in each regression. Fund style fixed effects are included in all specifications. The t-statistics reported are calculated using standard errors clustered at style-year level.

m	Coef.	t-stat	N	Adj. Rsq.
Panel A: Return in Excess of MKT				
12	-0.123	-1.19	2,801	0.022
24	-0.099	-1.28	2,801	0.025
36	-0.097	-1.63	2,801	0.031
60	-0.111	-2.52	2,801	0.043
Panel B: CAPM Alpha				
12	-0.146	-1.44	2,801	0.018
24	-0.131	-1.67	2,801	0.022
36	-0.107	-1.78	2,801	0.024
60	-0.130	-2.97	2,801	0.035
Panel C: Fama-French 3-Factor Alpha				
12	-0.169	-2.39	2,801	0.019
24	-0.124	-2.59	2,801	0.031
36	-0.112	-2.95	2,801	0.032
60	-0.078	-2.90	2,801	0.021
Panel D: Carhart 4-Factor Alpha				
12	-0.140	-2.04	2,801	0.018
24	-0.112	-2.36	2,801	0.025
36	-0.094	-2.76	2,801	0.020
60	-0.064	-2.74	2,801	0.011

Table 1.18: Measuring Style Performance Using CAPM Alpha: Regressions of Post-Entry Fund Performance on Past Style Performance

This table reports results of regressions of fund performance in the m months following its entry on past style performance. The dependent variables are measured by differences in return in excess of the value-weighted CRSP index return, the CAPM alpha, the Fama-French 3-factor alpha, and the Carhart 4-factor alpha between the entrant fund and the value-weighted average of incumbent funds in the same style category. The independent variable is Carhart 4-Factor alpha of value-weighted average returns of funds of the same style in the past 24 months. Each fund entry during the period of 1991–2015 contributes to one observation in each regression. Fund style fixed effects are included in all specifications. The t-statistics reported are calculated using standard errors clustered at style-year level.

m	Coef.	t-stat	N	Adj. Rsq.
Panel A: Return in Excess of MKT				
12	-0.229	-1.10	2,801	0.025
24	-0.255	-1.54	2,801	0.036
36	-0.244	-1.83	2,801	0.046
60	-0.225	-2.42	2,801	0.060
Panel B: CAPM Alpha				
12	-0.249	-1.19	2,801	0.022
24	-0.285	-1.71	2,801	0.036
36	-0.271	-1.99	2,801	0.046
60	-0.261	-2.81	2,801	0.060
Panel C: Fama-French 3-Factor Alpha				
12	-0.347	-3.00	2,801	0.031
24	-0.314	-4.19	2,801	0.058
36	-0.259	-4.21	2,801	0.056
60	-0.145	-3.54	2,801	0.031
Panel D: Carhart 4-Factor Alpha				
12	-0.322	-2.85	2,801	0.030
24	-0.302	-4.10	2,801	0.053
36	-0.231	-4.13	2,801	0.044
60	-0.125	-3.53	2,801	0.019

Table 1.19: Robustness: Comparing Post-Entry Performance of Hot and Cold Style Entrant Funds, Dependent Sort on Size and Book-to-Market Styles

An investment style is considered as in hot status if the TNA-weighted average returns of funds in the style category minus the value-weighted CRSP index return in the previous 24 months is above the time-series median of the entire sample. An entrant fund is considered as a hot style entrant fund if its initial holding-based style at the time of its entry is in hot status. Post-entry performance is measured over the 36-month window after the month of the funds' inception date. If the fund is closed within the 36 months, it is still included in the calculation. Return in excess of MKT is measured as the average fund monthly return over the value-weighted CRSP index return. *t*-statistics of two sample mean tests are reported for the difference between average performance of hot and cold style entrant funds. The sample period is 1991–2015.

		Small			Mid			Large		
	All	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
Panel A: Number of Entrants										
Hot	1,512	238	220	220	156	138	181	129	101	129
Cold	1,289	148	142	173	154	126	110	136	166	134
Total	2,801	386	362	393	310	264	291	265	267	263
Panel B: Return in Excess of MKT										
Hot	-0.023	0.048	0.106	0.086	-0.164	-0.076	0.072	-0.211	-0.184	-0.155
Cold	-0.010	0.226	0.191	-0.012	0.018	-0.004	-0.028	-0.120	-0.192	-0.170
Difference	-0.013	-0.179	-0.085	0.098	-0.182	-0.072	0.100	-0.091	0.009	0.015
t-stat	-0.508	-1.923	-1.065	1.186	-2.949	-0.904	1.431	-1.718	0.135	0.236

(continued)

		Small			Mid			Large		
	All	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
Panel C: CAPM Alpha										
Hot	-0.029	0.013	0.057	0.023	-0.168	-0.056	0.079	-0.164	-0.123	-0.093
Cold	0.025	0.259	0.172	0.039	0.023	0.056	0.004	-0.092	-0.106	-0.137
Difference	-0.054	-0.245	-0.116	-0.016	-0.192	-0.112	0.075	-0.072	-0.017	0.044
t-stat	-2.262	-2.533	-1.528	-0.206	-3.230	-1.513	1.238	-1.621	-0.358	0.847
Panel D: Fama-French 3-Factor Alpha										
Hot	-0.052	0.059	0.005	-0.055	-0.118	-0.105	-0.067	-0.096	-0.099	-0.109
Cold	0.014	0.300	0.096	-0.032	0.049	0.040	-0.031	-0.049	-0.096	-0.160
Difference	-0.065	-0.241	-0.091	-0.023	-0.167	-0.145	-0.036	-0.047	-0.003	0.051
t-stat	-3.119	-2.672	-1.417	-0.420	-2.809	-2.232	-0.693	-1.198	-0.075	1.096
Panel E: Carhart 4-Factor Alpha										
Hot	-0.066	-0.003	-0.022	-0.053	-0.126	-0.112	-0.053	-0.102	-0.087	-0.120
Cold	0.010	0.222	0.088	0.003	0.018	-0.002	0.028	-0.066	-0.086	-0.116
Difference	-0.076	-0.225	-0.110	-0.056	-0.144	-0.110	-0.081	-0.036	-0.001	-0.005
t-stat	-3.888	-2.711	-1.828	-1.043	-2.667	-1.839	-1.643	-0.924	-0.022	-0.124

Table 1.20: Robustness: Comparison of Returns on Buy-and-Hold Portfolios of Hot and Cold Style Entrant Funds, Dependent Sort on Size and Book-to-Market Styles

This table reports results of time-series regressions of monthly returns of buy-and-hold portfolios of entrant funds on Carhart 4-factors. For the sample period between 1991 and 2018, each entrant fund is added to the hot or non-hot fund portfolio and held for 5 years. Equally weighted portfolios are rebalanced at the end of every year. For individual portfolios, the following time-series regression is estimated:

$$R_{p,t} - R_{f,t} = a + b \cdot RMRF_t + h \cdot HML_t + s \cdot SMB_t + u \cdot UMD_t + e_t.$$

To estimate the difference in performance between hot and non-hot portfolios, the difference in returns of the two portfolios is used as the dependent variable. t-statistics of coefficient estimates are in parentheses. Each regression uses 336 monthly observations.

	Coefficient Estimates					
	a	b	h	s	u	Adj. Rsq.
Panel A: Equally Weighted Portfolio Returns						
Hot	-0.08	0.99	-0.01	0.25	0.00	0.98
	(-2.25)	(106.18)	(-0.50)	(21.10)	(0.16)	
Cold	-0.06	0.95	0.05	0.20	0.01	0.98
	(-1.95)	(122.64)	(4.99)	(20.45)	(1.71)	
Difference	-0.02	0.05	-0.06	0.05	-0.01	0.28
	(-0.72)	(5.54)	(-5.21)	(4.76)	(-1.41)	
Panel B: Value Weighted Portfolio Returns						
Hot	-0.16	0.99	-0.04	0.27	0.02	0.97
	(-3.59)	(89.75)	(-2.64)	(19.16)	(2.15)	
Cold	-0.07	0.99	-0.02	0.16	0.04	0.98
	(-1.99)	(112.39)	(-1.76)	(13.80)	(4.92)	
Difference	-0.09	0.00	-0.02	0.12	-0.02	0.19
	(-1.99)	(0.08)	(-1.23)	(8.11)	(-1.77)	

Table 1.21: Comparing Post-Entry Performance of Hot and Cold Style Entrant Funds, One-Dimensional Style Categories

An investment style is considered as in hot status if the TNA-weighted average returns of funds in the style category minus the value-weighted CRSP index return in the previous 24 months is above the time-series median of the entire sample. An entrant fund is considered as a hot style entrant fund if its initial holding-based style at the time of its entry is in hot status. Post-entry performance is measured over the 36-month window after the month of the funds' inception date. If the fund is closed within the 36 months, it is still included in the calculation. Return in excess of MKT is measured as the average fund monthly return over the value-weighted CRSP index return. *t*-statistics of two sample mean tests are reported for the difference between average performance of hot and non-hot entrant funds. Each entrant funds from 1991 to 2015 contribute to one observation for the test.

		Book-to-Market			Size		
	All	Growth	Blend	Value	Small	Mid	Large
			Panel A: Number of Entrants				
Hot	1,463	570	401	492	672	450	341
Cold	1,338	436	484	418	469	415	454
Total	2,801	1,006	885	910	1,141	865	795
			Panel B: Return in Excess of MKT				
Hot	-0.035	-0.050	-0.054	-0.002	0.064	-0.063	-0.194
Cold	0.002	0.113	-0.032	-0.074	0.147	0.011	-0.155
Difference	-0.037	-0.163	-0.022	0.072	-0.083	-0.074	-0.039
t-stat	-1.458	-3.496	-0.523	1.645	-1.689	-1.831	-1.113

(continued)

	All	Book-to-Market			Size		
		Growth	Blend	Value	Small	Mid	Large
Panel C: CAPM Alpha							
Hot	-0.043	-0.071	-0.051	-0.004	0.008	-0.057	-0.126
Non-hot	0.038	0.145	0.000	-0.032	0.181	0.041	-0.113
Difference	-0.080	-0.217	-0.051	0.028	-0.172	-0.097	-0.012
t-stat	-3.363	-4.647	-1.356	0.744	-3.602	-2.630	-0.447
Panel D: Fama-French 3-Factor Alpha							
Hot	-0.048	-0.002	-0.072	-0.082	0.005	-0.092	-0.095
Non-hot	0.007	0.126	-0.007	-0.099	0.112	0.013	-0.107
Difference	-0.055	-0.128	-0.064	0.017	-0.108	-0.105	0.012
t-stat	-2.638	-2.937	-1.998	0.589	-2.606	-3.105	0.476
Panel E: Carhart 4-Factor Alpha							
Hot	-0.060	-0.035	-0.077	-0.074	-0.021	-0.092	-0.092
Non-hot	0.001	0.079	-0.020	-0.057	0.092	0.006	-0.098
Difference	-0.061	-0.114	-0.057	-0.017	-0.114	-0.098	0.006
t-stat	-3.118	-2.867	-1.866	-0.627	-2.947	-3.155	0.260

Table 1.22: Comparing Performance of Equally Weighted Buy-and-Hold Portfolios of Hot and Cold Style Entrant Funds

This table reports performance of equally weighted buy-and-hold portfolios of entrant funds. For the sample period between 1991 and 2018, each entrant fund is added to the hot or non-hot fund portfolio and held for 5 years. Equally weighted portfolios are rebalanced at the end of every year. For individual portfolios, the following time-series regression is estimated:

$$R_{p,t} - R_{f,t} = a + b \cdot RMRF_t + h \cdot HML_t + s \cdot SMB_t + e_t.$$

To estimate the difference in performance between hot and non-hot portfolios, the difference in returns of the two portfolios is used as the dependent variable. Only the intercept is included to measure performance using excess returns, the first two terms are included for CAPM, and all terms are included for the Fama-French 3-factor model. t-statistics of coefficient estimates are in parentheses. Each regression uses 336 monthly observations.

	Coefficient Estimates				
	a	b	h	s	Adj. Rsq.
Panel A: Excess Returns					
Hot	0.62				
	(2.54)				
Cold	0.64				
	(2.83)				
Difference	-0.02				
	(-0.53)				
Panel B: CAPM					
Hot	-0.08	1.04			0.94
	(-1.41)	(74.60)			
Cold	-0.02	0.97			0.96
	(-0.36)	(89.68)			
Difference	-0.07	0.07			0.18
	(-1.94)	(8.51)			
Panel C: Fama-French 3-Factor Model					
Hot	-0.10	0.99	-0.01	0.27	0.98
	(-2.67)	(114.87)	(-1.07)	(23.30)	
Cold	-0.04	0.94	0.04	0.20	0.98
	(-1.36)	(127.05)	(4.16)	(20.61)	
Difference	-0.05	0.05	-0.06	0.07	0.36
	(-1.77)	(6.96)	(-5.46)	(6.62)	

Table 1.23: Comparing Performance of Value Weighted Buy-and-Hold Portfolios of Hot and Cold Style Entrant Funds

This table reports performance of value weighted buy-and-hold portfolios of entrant funds. For the sample period between 1991 and 2018, each entrant fund is added to the hot or non-hot fund portfolio and held for 5 years. For individual portfolios, the following time-series regression is estimated:

$$R_{p,t} - R_{f,t} = a + b \cdot RMRF_t + h \cdot HML_t + s \cdot SMB_t + e_t.$$

To estimate the difference in performance between hot and non-hot portfolios, the difference in returns of the two portfolios is used as the dependent variable. Only the intercept is included to measure performance using excess returns, the first two terms are included for CAPM, and all terms are included for the Fama-French 3-factor model. t-statistics of coefficient estimates are in parentheses. Each regression uses 336 monthly observations.

	Coefficient Estimates				
	a	b	h	s	Adj. Rsq.
Panel A: Excess Returns					
Hot	0.55				
	(2.23)				
Cold	0.63				
	(2.70)				
Difference	-0.08				
	(-1.45)				
Panel B: CAPM					
Hot	-0.16	1.05			0.93
	(-2.34)	(66.16)			
Cold	-0.05	1.00			0.96
	(-1.08)	(92.04)			
Difference	-0.11	0.05			0.04
	(-2.07)	(3.82)			
Panel C: Fama-French 3-Factor Model					
Hot	-0.16	1.00	-0.06	0.26	0.96
	(-3.27)	(86.53)	(-3.48)	(16.65)	
Cold	-0.05	0.97	-0.04	0.16	0.98
	(-1.35)	(112.49)	(-3.16)	(13.72)	
Difference	-0.11	0.03	-0.02	0.10	0.15
	(-2.20)	(2.36)	(-1.09)	(6.23)	

Table 1.24: Industry Composition

This table reports the average weight of stocks of the ten industry classification in the market and the initial portfolios of entrant funds. The sample period is 1991–2015. All numbers are in percentage points.

Ten Industry Classifications	Market	Entrant Funds	
		Unnormalized	Normalized
1. Consumer non-durables	7.35	5.98	6.66
2. Consumer durables	4.00	3.77	4.13
3. Healthcare	9.92	8.68	9.56
4. Manufacturing	13.05	14.05	15.52
5. Energy	7.45	5.22	5.87
6. Utilities	4.18	2.80	3.18
7. Telecom	6.08	3.81	4.21
8. Business equipment and services	20.01	20.74	22.73
9. Wholesale and retail	10.37	10.96	12.06
10. Finance	17.61	14.52	16.09
Total	100.00	90.53	100.00

Table 1.25: Comparing Post-Entry Performance of Hot and Cold Industry Entrant Industry Concentrated Funds

This table compares post-entry performance of funds that concentrated in hot and cold industries. An entrant fund is considered as concentrated in an industry if the weight of the industry in its initial portfolio holdings is more than three times of the market weight or is over 50%. An industry is considered as hot if the CAPM alpha of the industry return in the past 24 month is above the time-series median. Post-entry performance is measured over the 36-month following the fund inception date. If the fund is closed within the 36 months, it is still included in the calculation. The sample period is 1991–2015.

		Ten Industry Classification									
	All	1	2	3	4	5	6	7	8	9	10
Panel A: Number of Entrants											
Hot	251	31	5	13	25	18	21	13	98	19	8
Cold	223	32	6	7	22	13	11	15	68	40	9
Total	474	63	11	20	47	31	32	28	166	59	17
Panel B: CAPM Aplha											
Hot	0.016	0.022	0.149	-0.177	0.211	-0.037	0.079	0.280	-0.009	-0.219	-0.005
Cold	0.232	0.186	-0.120	0.243	-0.137	0.075	0.202	0.155	0.410	0.234	0.559
Difference	-0.216	-0.164	0.269	-0.420	0.348	-0.112	-0.123	0.125	-0.419	-0.453	-0.564
t-stat	-2.693	-1.030	1.198	-1.329	1.345	-0.304	-0.746	0.373	-2.652	-1.670	-2.149
Panel C: Fama-French 3-Factor Alpha											
Hot	0.005	-0.082	0.033	-0.125	0.073	-0.109	-0.043	0.194	0.075	-0.160	-0.068
Cold	0.249	0.056	-0.171	0.164	-0.152	0.105	0.075	0.001	0.607	0.243	0.406
Difference	-0.244	-0.139	0.203	-0.290	0.225	-0.214	-0.118	0.193	-0.532	-0.403	-0.474
t-stat	-3.227	-1.114	0.959	-0.862	0.981	-0.628	-0.670	0.699	-3.588	-1.514	-2.055
Panel D: Carhart 4-Factor Alpha											
Hot	-0.019	-0.092	0.016	-0.096	0.035	-0.082	-0.072	0.136	0.023	-0.143	0.008
Cold	0.214	0.080	-0.090	0.124	0.007	0.181	0.116	-0.019	0.419	0.236	0.378
Difference	-0.233	-0.173	0.106	-0.220	0.028	-0.263	-0.189	0.155	-0.396	-0.379	-0.370
t-stat	-3.395	-1.411	0.488	-0.804	0.122	-0.811	-1.057	0.627	-2.934	-1.572	-1.717

Table 1.26: Regressions of Post-Entry Performance on Hot Industry Dummy Variable

This table reports results of regressions of fund performance in the m months following its entry on on a dummy variable that equals one if the entrant fund is concentrated in a hot industry at the time of entry. The dependent variables are measured by the CAPM alpha, the Fama-French 3-factor alpha, and the Carhart 4-factor alpha. The sample period is 1991–2015. Industry fixed effects are included in all specifications. The t-statistics reported are calculated using standard errors clustered at industry-year level.

m	Coef.	t-stat	N	Adj. Rsq.
Panel A: CAPM Alpha				
12	0.047	0.16	474	0.011
24	-0.124	-0.67	474	0.006
36	-0.225	-1.90	474	0.022
60	-0.239	-2.68	474	0.027
Panel B: Fama-French 3-Factor Alpha				
12	-0.113	-0.63	474	0.006
24	-0.241	-2.11	474	0.019
36	-0.264	-2.87	474	0.032
60	-0.230	-3.66	474	0.039
Panel C: Carhart 4-Factor Alpha				
12	-0.025	-0.14	474	0.006
24	-0.201	-2.02	474	0.011
36	-0.244	-3.48	474	0.017
60	-0.202	-3.91	474	0.021

Table 1.27: Comparing Post-Entry Performance of Hot and Cold Dividend Yield Style Entrant Funds

This table compares post-entry performance hot and cold style entrant funds. Entrant funds are categorized as high or low dividend yield styles by whether the holdings value-weighted average dividend yield of their holdings are above or below the cross section median of existing funds. A style is considered as hot if the excess return in the past 24 month is above the time-series median. Post-entry performance is measured over the 36-month following the fund inception date. If the fund is closed within the 36 months, it is still included in the calculation. The sample period is 1991–2015.

	All	Low D/P	High D/P
Panel A: Number of Entrants			
Hot	1,569	870	699
Cold	1,232	528	704
Total	2,801	1,398	1,403
Panel B: Return in Excess of MKT			
Hot	-0.071	-0.089	-0.048
Cold	0.051	0.180	-0.046
Difference	-0.121	-0.268	-0.002
t-stat	-4.713	-6.403	-0.065
Panel C: CAPM Alpha			
Hot	-0.040	-0.083	0.014
Cold	0.040	0.102	-0.006
Difference	-0.080	-0.185	0.020
t-stat	-3.313	-4.508	0.766
Panel D: Fama-French 3-Factor Alpha			
Hot	-0.062	-0.055	-0.070
Cold	0.030	0.190	-0.091
Difference	-0.092	-0.246	0.021
t-stat	-4.357	-6.584	1.048
Panel E: Carhart 4-Factor Alpha			
Hot	-0.076	-0.083	-0.068
Cold	0.027	0.126	-0.048
Difference	-0.103	-0.209	-0.020
t-stat	-5.296	-6.109	-1.031

Table 1.28: Regressions of Post-Entry Performance on Hot Dividend Yield Style Dummy Variable

This table reports results of regressions of fund performance in the m months following its entry on on a dummy variable that equals one if the entrant fund adopts a hot dividend yield style. The dependent variables are measured by the CAPM alpha, the Fama-French 3-factor alpha, and the Carhart 4-factor alpha. The sample period is 1991–2015. Style fixed effects are included in all specifications. The t-statistics reported are calculated using standard errors clustered at style-year level.

m	Coef.	t-stat	N	Adj. Rsq.
Panel A: Return in Excess of MKT				
12	-0.042	-0.28	2,801	0.004
24	-0.098	-0.70	2,801	0.004
36	-0.131	-1.41	2,801	0.010
60	-0.146	-2.33	2,801	0.019
Panel B: CAPM Alpha				
12	0.015	0.14	2,801	0.002
24	-0.024	-0.21	2,801	0.000
36	0.079	-0.97	2,801	0.003
60	-0.145	-2.52	2,801	0.021
Panel C: Fama-French 3-Factor Alpha				
12	0.003	0.05	2,801	0.005
24	-0.083	-1.19	2,801	0.013
36	-0.108	-1.73	2,801	0.020
60	-0.079	-1.83	2,801	0.012
Panel D: Carhart 4-Factor Alpha				
12	0.045	0.75	2,801	0.005
24	-0.078	-1.26	2,801	0.009
36	-0.112	-2.25	2,801	0.013
60	-0.074	-2.26	2,801	0.007

Chapter 2

Fund Flows in the Shadow of Stock Trading Regulation: Evidence from China

2.1 Introduction

Stock exchanges and regulators around the world widely adopt polices that constrain trading activities under certain circumstances, with the intention of protecting investors of the markets they regulate. Two prominent examples of these regulatory policies are trading halts and trading suspensions.[1] Such regulations prevent insider trading and market manipulation by temporarily preventing the trading of stocks. However, they might not completely eliminate the liquidity of targeted assets in today's complex financial markets. In particular, although polices can effectively restrict transactions in exchanges or over-the-counter markets, there is still transformed liquidity provided by other investment vehicles, such as open-end mutual funds.[2] This fact creates the possibility that regulatory policies targeting one market may indirectly affect investors in other markets, thereby complicating the cost-benefit analysis at the aggre-

[1]The largest 10 stock exchanges by total market capitalization of listed stocks as of 2019 are NYSE, NASDAQ, Tokyo Stock Exchange, Shanghai Stock Exchange, Hong Kong Stock Exchange, Euronext, London Stock Exchange, Shenzhen Stock Exchange, Toronto Stock Exchange, and Bombay Stock Exchange. All of these exchanges and their regulators have rules for trading halts, trading suspensions, or both.

[2]Existing studies mostly examine the direct effects on the markets targeted by such regulations. For example, Subrahmanyam (1994), Lee, Ready, and Seguin (1994), Corwin and Lipson (2000), Christie, Corwin, and Harris (2002) study the effects of trading halts in stock markets.

gate level. Thus, recognizing such potential regulatory spillover effects serves as a crucial step towards achieving a better regulatory framework for modern financial markets.

In this study, we document evidence for the effects of stock trading suspensions on the behavior of mutual fund investors in China. The Chinese stock and mutual fund markets provide a desirable setting for this purpose because of the prevalence and long duration of trading suspension events. Both of the two national stock exchanges, the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE), have been persistently implementing the rules that suspend the trading of individual stocks prior to major corporate events.[3] During the suspension period, firms are required to periodically disclose the progress of the ongoing events, revealing information material to firm valuations. Since investors cannot trade the stocks, the information is not incorporated into stock prices, rendering the prices stale. For mutual funds that hold suspended stocks, this in turn leads to staleness of their net asset values (NAVs) because of the difficulty in making timely and precise adjustments to NAVs. The disparities between the perceived values of a fund's stock holdings and the fund's NAV calculated using stale stock prices give rise to predictable future NAV variations: Once trading resumes, stock prices and fund NAVs will quickly move towards levels that reflect existing information. Such anticipated changes in NAVs can potentially distort fund investors' behaviors.

Using a comprehensive sample of stock trading suspension events and mutual fund portfolio holdings during 2004-2018, we find that the highly dispersed stock returns

[3]For example, the SSE's Stock Listing Rules (2001) allows the exchange or the China Securities Regulatory Commission (CSRC) to execute stock trading suspensions in various scenarios, including merger, acquisition, asset sales and debt restructuring.

following trading resumptions indeed exert substantial impact on fund NAVs. Given this fact, we hypothesize that investors' money flows positively respond to the unrealized impacts of suspended portfolio stocks on future fund NAVs. To test this relation, we construct an empirical measure, *Resumption Impact*, as the product of the suspended stock's weight in the fund portfolio observed by investors and post-resumption stock return. This measure captures the direction and magnitude of the unrealized impact of firm-specific information on fund NAV. Consistent with our hypothesis, we find a statistically and economically significant positive response of fund flows to resumption impact of suspended stocks held by mutual funds. On average, a 1% future impact on fund NAV during the first week of trading resumption is associated with 1.1 percentage point increase in net flows during the quarter before the impact realizes. This result implies that in the presence of trading suspension rules, fund investors combine both firm-specific information and fund portfolio disclosure to make investment decisions.

Among trading suspension events with good and bad news, when are fund flows more responsive to the resumption impact? The heterogeneity in responses is interesting because fund inflows and outflows have different implications on investor welfare and market stability. Specifically, the opportunistic fund flows induced by trading suspensions tend to dilute future fund investment profits and concentrate future fund investment losses, both at the expense of long-term fund investors. The first-mover advantage of moving money out of a fund that holds suspended stocks facing negative information and over-priced NAV introduces payoff complementarity among fund investors (Chen, Goldstein, and Jiang, 2010). Such a mechanism may exacerbate the risk of mutual fund run, even in absence of flow-induced trade by the fund manager. Empirically, we find

that fund flows are highly sensitive to large positive resumption impacts, while the sensitivities are similar in other cases. This finding suggests that the indirect effect of trading suspensions is particularly strong when money of outside investors flows into funds that hold suspended stocks with impactful good firm-specific news.

To provide further support for the interpretation that the flow response we document is driven by investors' investigation of suspended stocks in disclosed fund portfolios, we develop two placebo tests. These tests exploit institutional facts on differential timings and scopes of quarterly, semi-annual and annual fund disclosure reports. The first test shows that fund flows do not appear to respond to future resumption impact if the suspended stock is held by the fund at the end of the quarter just prior to trading resumption, but is not held at the end of the previous quarter. The absence of flow response in this case is likely because investors can only observe the most recent end-of-quarter holdings snapshot when making investment decisions. In the second test, we find that fund flows do not respond to the resumption impact of non-top-10 stock holdings disclosed in fund annual reports, which are published with a delay up to 90 business days.[4] Therefore mutual fund portfolio disclosure serves as the channel through which stock trading suspensions affect fund investor behaviors.

This study contributes to studies of trading regulations by focusing on the indirect effects on the behaviors of investors in the open-end mutual fund market. We show that trading suspension policy induces opportunistic fund investors to purchase and redeem fund shares to exploit stale fund NAVs. Such "informed flows" earn better

[4]Section 2 explains mandatory disclosure requirements on Chinese mutual funds.

returns at the cost of buy-and-hold investors. Considering the costly search process of investigating firm announcements and fund portfolio holdings, trading suspension could lead to a net welfare loss among aggregate fund investors. Therefore, our findings call for a better integrated regulatory framework that takes the potential spillovers of policies into account. The evidence documented here is related to the "whack-a-mole" game that Cai, He, Jiang, and Xiong (2017) use in describing the spillover effects of increased stock transaction tax on trading activities in the warrant market.

Our study is related to a large literature on investor flows to asset managers as surveyed by Christoffersen, Musto, and Wermers (2014), especially papers that study the flows that exploit stale fund NAVs (Chalmers, Edelen, and Kadlec, 2001; Goetzmann, Ivković, and Rouwenhorst, 2001; Boudoukh, Richardson, Subrahmanyam, and Whitelaw, 2002; Greene and Hodges, 2002; Zitzewitz, 2006; Choi, Kronlund, and Oh, 2019). In these papers, stale NAVs arise from non-synchronous trading or the illiquid nature of portfolio securities. Our study differs from existing research by studying a setting in which the staleness of NAVs comes as an unintended consequence of stock trading regulations.

Two existing papers also examine the effects of stock trading suspensions in the Chinese market. Huang, Shi, Song, and Zhao (2018) study the determinants of trading suspension and document the trading patterns and performance of stock investors during the 2015 market crash. Liu, Xu, and Zhong (2017) show that trading restrictions can lead to negative contagion during stock market crash episodes because fund managers facing redemption pressure are forced to sell portfolio stocks that are not suspended. Instead of stock investors or fund managers who directly trade stocks, this study focuses on fund

flows as responses to firm-specific news during trading suspensions. We evaluate this economic channel over 14 years of sample period and our results are robust to exclusion of the 2015 market crash period.

The remainder of this paper proceeds as follows. Section 2.2 summarizes the institutional background of the empirical setting, and Section 2.3 explains our sample and empirical measures. Section 2.4 presents the results of the main empirical tests. Section 2.5 performs additional tests for robustness and Section 2.6 concludes.

2.2 Institutional Background

2.2.1 Stock Trading Suspension

Since the 1990s, trading suspension has been a common policy tool in the Chinese stock market. Regulators require firms whose equity shares are publicly traded on China's Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE) to apply for trading suspensions when they prepare for major corporate events. Without any strict implementation rule, Chinese public firms can discretionarily apply for trading suspensions to prevent information leakage before the announcements of corporate events. In practice, firms also take advantage of this regulatory policy to prevent the trading of their stocks for other purposes.[5]

2.2.2 Mutual Funds in China

Since its inception in 1998, the Chinese mutual fund industry has experienced fast growth along with the economy. According to the Asset Management Association

[5]See Huang, Shi, Song, and Zhao (2018) for more detailed discussion.

of China, by the end of June of 2018, the size of total assets under management reached 12.7 trillion CNY (approximately 1.8 trillion USD). Similar to mutual funds in the US market, equity shares of publicly traded domestic firms serve as one of the major financial asset classes held by Chinese funds.

The China Securities Regulatory Commission (CSRC) requires mutual funds to publicly disclose their portfolio holdings since 2004. Regulatory rules mandate six reports every year. In each of the four quarterly reports, mutual funds disclose only the top-10 stock holdings. In contrast, full stock portfolios at the end of June and December are disclosed in the semiannual and annual reports. The timeliness of these reports also differ: the maximum number of days allowed between the end of period and the disclosure for quarterly reports are 15 business days, while the corresponding intervals are 60 calendar days and 90 calendar days for semiannual and annual reports, respectively.

2.3 Data

We combine multiple datasets of mutual fund and stock market information from the China Stock Market & Accounting Research (CSMAR) database. This section describes our sample and empirical measures.

2.3.1 Mutual Funds

CSMAR provides comprehensive coverage of both operating and defunct mutual funds domiciled in China. We obtain data on fund return, net asset value (NAV), net assets, portfolio holdings, and other information contained in fund quarterly and semi-annual reports. We focus on open-end mutual funds that directly hold stocks and are

traded mainly through investors' direct fund share purchase and redemption. Therefore, we drop funds that are classified as exchange-traded funds (ETFs), listed open-end funds (LOFs), or funds of funds (FOFs). We also exclude funds that have more than one share classes because these are primarily structured funds whose share classes have very different exposures to the fund portfolios (Li, 2017). These filters leave us with 2,550 unique funds.

Fund return and NAV are observed at the daily frequency, while net assets are observed at the quarterly frequency. We compute quarterly fund-level flow as

$$Flow_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1} \times (1 + r_{j,t})}{TNA_{j,t-1} \times (1 + r_{j,t})}, \tag{2.1}$$

where $TNA_{j,t}$ is the total net assets of fund j at the end of quarter t, and $r_{j,t}$ is the return earned by fund investors from the end of quarter $(t-1)$ to the end of quarter t. By construction, this flow measure is bounded from below by -1. Following the literature, we trim the flows at 1% and 99% to avoid the influence of extreme net flows on our results.

Starting from July 2004, funds are required by CSRC to disclose their top-10 stock holdings in their quarterly reports, and full portfolio holdings in semi-annual and annual reports. Therefore, we set our sample period as 2004Q3-2018Q2. We use the top-10 quarterly stock holdings in our main results primarily for the measurement of fund flow. We use the full portfolio holdings in our extended tests. The semi-annual and annual reports also include decomposition of fund ownership by individual and institutional investor clienteles.

2.3.2 Stocks

We consider all A Share stocks ever listed on the main board of the Shanghai Stock Exchange (SSE), the main board, Growth Enterprise Market (GEM) board or Small/Medium Enterprise (SME) board of the Shenzhen Stock Exchange (SZSE). This results in 3,636 stocks and they account for more than 95% of equity holdings of sample funds. CSMAR collects all trading suspension incidences from public announcements posted to the stock exchanges. The dataset includes the dates and times of the announcements of trading suspension and subsequent resumption events.

During our sample period, 3,437 out of the 3,636 sample stocks experienced at least one instance of a trading suspension. In total, there are 97,934 suspension events. The duration of suspension ranges from 0 to 1,679 trading days. Intraday trading suspension events usually happen during the hour of mandatory corporate disclosure or follow large price volatility. These suspension events are short-lived and are less relevant for the purpose of this study, so we exclude them from the sample. This filter leaves us with 16,611 stock suspension events. In 5,063 events, the stocks involved are suspended from trading for at least 21 trading days (about one calendar month).

For suspension events with relatively longer period, firms typically make a sequence of public announcements on the progress of the corporate events. Trading resumptions usually follow the announcements of eventual outcomes with some lag. Besides, firms typically announce future resumption dates publicly before they happen. This timing feature gives fund investors sufficient time to digest the new information.

2.3.3 Return

We measure stock returns and mutual fund performance using both raw returns and abnormal returns adjusted for the exposure to stock market movements. We obtain daily stock returns directly from the CSMAR database, and calculate daily fund returns using data on daily NAVs, adjusting for fund share splits and distributions. To compute market-adjusted daily abnormal returns for stocks and mutual funds, we estimate the market beta with a rolling regression for each stock- and fund-quarter using 100 non-missing daily returns prior to the beginning of the quarter. For all days in the quarter, we calculate abnormal returns as out-of-sample alphas using these estimated betas and realized market returns. We use the CSI 300 index return as a proxy for the stock market return, and one-year bank deposit interest rate as the risk-free rate. For mutual funds, we additionally control for the return exposure to aggregate bond market return proxied by the CSI Aggregate Bond Index return since many mutual funds also invest in bonds.

2.3.4 Resumption Impact

Trading suspension events are typically associated with public announcements of major firm-specific events, and stock prices often exhibit large variations immediately following trading resumptions. While suspended stocks can not be traded during suspension periods and the market prices of these stocks are largely fixed at the pre-suspension levels, NAVs of mutual funds are calculated based on market price of portfolio assets on a daily basis and investors can purchase and redeem at the NAVs calculated on each trading day. When funds hold large proportion of stocks that experience trading suspensions, their NAVs can be substantially affected by post-resumption stock returns.

Investors can potentially profit from short-term stock mispricing due to trading suspension by investing in the mutual funds that hold sizable positions in these stocks based on announced firm-specific information. For this to be feasible, a necessary condition is that the resumption impact is large enough to not be washed away by price variations of other portfolio stocks, and the fund does not properly adjust stock valuation during suspension period.

To empirically validate the influence of post-resumption stock returns on fund returns, we construct a fund-stock-level measure to capture the impact of post-resumption stock price variations on fund NAV:

$$RI_{i,j,t} \;=\; Weight_{i,j,t} \times Return_{i,t}^{[\tau,\tau+\Delta\tau]}, \tag{2.2}$$

where $Weight_{i,j,t}$ is fund j's portfolio weight of suspension stock i at the end of quarter t, and $Return_{i,t}^{[\tau,\tau+\Delta\tau]}$ is stock i's return over $\Delta\tau$ horizon from resumption date τ in the next quarter. Specifically, we first select all trading suspension events that last at least one day, and match them by resumption dates to all quarterly fund holding records with at least a 1% portfolio weight. To ensure that the stock is certainly held by the fund before resumption, we require that trading suspensions must happen before the end of the quarter prior to resumption.[6] Next, we match each resumption date to daily fund share class cumulative NAVs and daily adjusted stock prices to compute both post-resumption returns over $\Delta\tau = 1, 2, 3, 5, 7, 10$ and 15 trading days.

We examine the correlation between fund returns and the resumption impact measure for trading suspension events in our sample. Figure 2.2 plots that fund return

[6]We only observe stock holdings at the end of quarters. If we also include suspension events that occur after holding snapshot dates, results are qualitatively and quantitatively similar.

and stock resumption impact are strongly positively correlated over the 5-day window following stock resumption. Table 2.1 further shows that this correlation holds for horizons ranging from 1 to 15 trading days, and the correlation is especially strong for cases where the funds are exposed to large post-resumption stock price variations. For example, the correlation between 5-day fund return and 5-day stock resumption impact following the resumption is 0.3 for the subsample where the magnitude of resumption impact is greater than 1%. Such events are not rare since we have 3,205 events like this in our sample. The correlation increases as we focus on subsamples with larger resumption impact. The correlation between fund return and stock resumption impact implies that investors can potentially exploit public firm-specific information by investing in funds that hold sizable positions in suspended stocks and benefit from the price movement of such stocks after they resume trading.

2.3.5 Sample Construction

We construct a panel dataset of fund-quarter observations following the timing convention illustrated in Figure 2.1. The 15-day delay in quarterly portfolio disclosure implies that investors can only observe stocks held by funds at the end of quarter $t-1$ when making decisions during quarter t. We use the post-resumption stock return realized after quarter t as a *proxy* for investor expectation on future stock price movements conditional on information observed by t. Suppose fund j is perceived to hold stock i that experiences suspension in quarter t and resumes during quarter $t+1$, we match $RI_{i,j,t}$ to fund level variables corresponding to quarter t. To be included in the sample, we require the gap between flow date t and resumption date τ to be no more than 2 months

(42 trading days) so that investors are likely to exploit disclosed firm-level information by t.[7] If more than one portfolio stocks experience trading suspension in a quarter, we aggregate $RI_{i,j,t}$ to the fund level by summing them up to reflect the overall impact on fund NAV. If none of the top-10 stock holdings involves suspension, we assign zero value to this measure for that fund-quarter. Finally, we exclude observations in which a fund manages less than 50 million CNY (approximately 7 million USD) or has an age less than 1 year. This leaves us with a sample of 26,211 fund-quarter observations.

Panel A of Table 2.2 reports summary statistics of our sample. Potentially due to the fast growth of this industry, overall existing mutual funds experience net money outflows, even though on average they generate 1.51% quarterly market-adjusted abnormal return before fees. An average fund has operated for around 5 years, with slightly more than 2 billion CNY (approximately 300 million USD) assets under management. In Panel B, only observations with at least one portfolio stock suspension events are reported. The resumption impact measured over short time windows has mean and median close to zero, but exhibit large dispersion, especially on both tails. This implies that observations with large exposure to post-resumption stock price jumps are associated with sizable changes on fund NAV once trading resumes. More than half of the sample funds, and most of fund families, experience resumption impact at least once. This fact allows us to examine investors' response to complicated information environment under general conditions.

[7] Section 5.4 show that our results are qualitatively and quantitatively similar if we change the filter to 1 month or 3 months.

2.4 Results

2.4.1 Baseline

We consider the following baseline regression specification to detect whether fund investors respond to firm-specific information of suspended stocks by purchasing or redeeming mutual fund shares:

$$Flow_{j,t} = \beta_1 \times RI_{j,t+1} + \Gamma \times Controls_{j,t-1} + \delta_t + \gamma_j + \varepsilon_{j,t}. \tag{2.3}$$

The main explanatory variable of interest, $RI_{j,t+1}$, is the fund-level *Resumption Impact* on fund j due to stocks that are perceived to be held by the fund and resume trading in quarter $t+1$. We adopt a time subscript $t+1$ for this variable because the returns on suspended stocks following their resumption used to construct this measure are calculated in quarter $t+1$. The portfolio weights are based on fund portfolio disclosure for the end of quarter $t-1$. RI is intended to capture the expected effect of suspended stocks on fund returns. Fund-level control variables include fund performance, log of fund size, log of fund age, log of fund family size, value-weighted average performance of other funds in the fund family, fund return volatility measured as standard deviation of trailing 12-month fund returns normalized to quarterly terms, purchase fee, redemption fee, and expense ratio. All control variables are lagged by one quarter. In addition, the specification includes fund fixed effects to absorb fund-level time invariant heterogeneities that affect flows, and time fixed effects to account for aggregate time-specific shocks that affect flows to all mutual funds.

Table 2.3 reports the results of the baseline regression. Column (1) shows that investors do respond to opportunities of trading suspended stocks through purchasing

and redeeming mutual fund shares. Controlling for fund performance in the recent past, fund-specific and time-specific constant factors that affect fund flows, *Resumption Impact* due to stock holdings that are expected to resume in the next quarter has a positive and significant influence on flows in the current quarter. The estimated coefficient remains similar in magnitude and significance when additional fund-level control variables are included in the regression, or when abnormal returns are used to measure stock and fund performance. Across all columns, we obtain coefficients on $RI(5d)$ close to 1. This implies that on average, an additional 1% of 5-day fund-level *Resumption Impact* is associated with an additional 1% quarterly fund flow. As an hypothetical example, suppose a fund holds a 10% position in a stock at the end of quarter $t-1$, the stock is suspended at the end of quarter t, and resumes trading in quarter $t+1$. If the stock earns 10% return over the 5 days following resumption, the fund would have experienced 1% higher flow during quarter t compared to an otherwise similar fund whose NAV is not affected by trading resumption of portfolio stocks.

2.4.2 When is Flow More Responsive to Resumption Impact?

Given the baseline results, a natural question is whether the flow response to *Resumption Impact* is mostly driven by events where the stock suspension events are associated with positive prospects or those come along with negative prospects. Theoretically, such two types of events differ in both potential responding investors and their incentives. For positive firm news, all investors can choose to invest money into the fund, and the money inflow dilutes existing buy-and-hold fund investors' value because fund NAVs do not reflect the value of suspended stocks in a timely manner. For negative

news, only existing fund shareholders can redeem money. The remaining fund investors can be hurt by redeeming investors because the latter group can redeem at NAVs higher than what would reflect the efficient price of suspended stocks in the fund portfolio. This mechanism could potentially amplify the flow-induced trades' market-destabilizing effects, as emphasized by Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2017). Given the important differences between these potential implications, we use several interaction specifications to examine how the flow response depends on *Resumption Impact*.

To do this, we augment the baseline specification with a dummy variable that equals one if *Resumption Impact* is positive and its interaction with the *Resumption Impact*.

$$Flow_{j,t} = \beta_1 \times RI_{j,t+1} + \beta_2 \times \mathbf{1}_{\{RI>0\}} + \beta_3 \times RI_{j,t+1} \times \mathbf{1}_{\{RI>0\}} + \Gamma \times Controls_{j,t-1} + \delta_t + \gamma_j + \varepsilon_{j,t}. \quad (2.4)$$

Moreover, we evaluate whether flows are more sensitive to impactful events by replacing $\mathbf{1}_{\{RI>0\}}$ with dummy variables *Left Tail* and *Right Tail*. These two variables are equal to one if *Resumption Impact* is larger than 3% or smaller than −3%, respectively.

The results of interaction specifications are reported in Table 2.4. Across all specifications, the coefficients on *Resumption Impact* are positive and statistically significant. The magnitudes are similar to those in the baseline results. For dummy variables *Positive* and *Left Tail*, the coefficients on the interaction term are statistically indistinguishable from zero, suggesting that the sensitivity of flow to suspended stocks associated with positive prospects and impactful negative events are similar to other events. In contrast,

for dummy variable *Right Tail*, the estimated coefficients are positive, significant and three to six times as large as the baseline estimate. Overall, the results in this table indicate that fund flow responds to both positive and negative *Resumption Impact* with similar magnitudes, but the response is particularly strong to impactful good news. This asymmetry in intensity of flow response is consistent with the notion that mutual fund shares cannot be short-sold, hence limiting the response to negative resumption impact. On the other hand, regardless of whether already holding the fund shares or not, both existing and new investors could respond to positive news by investing in the fund.

2.4.3 Portfolio Disclosure and Flow Responses

We interpret the results above as that investors investigate fund holdings and move money into or out of funds that hold suspended stocks based on firm-specific information announced during trading suspension. To lend further support to this interpretation, we develop two placebo tests that exploit two institutional features of Chinese mutual fund stock holdings disclosure rules: the timing of report publication, and the range of disclosure.

2.4.3.1 Unobserved Top-10 Holdings

One necessary condition for fund flows to respond to firm-specific information of suspended stocks is that fund investors *perceive* the fund to be holding the relevant stocks. It is important to recognize that for fund investors, the most timely information about fund stock holdings comes from disclosure reports corresponding to the previous

quarter-end.[8] Since investors cannot observe the actual stock holdings at the end of the current quarter, quarterly fund flows should not respond to firm news if the suspended stocks will have an impact on future NAV but were not on the top-10 holdings list at the end of the previous quarter.

To provide supporting evidence for this conjecture, we recalculate *Resumption Impact* using stocks that appear on holdings disclosed for the end of the concurrent quarter, but not on top-10 holdings disclosed for the previous quarter-end. These stock positions are *ex post* in the fund portfolios, but are not observed by investors while they make investment decisions during the current quarter. This modified measure is intended to capture the expected effects of suspended stocks on future fund NAV returns due to stocks that the funds actually hold but are *ex ante* unknown to investors.

Table 2.5 reports the results of regressing quarterly fund flows on the recalculated *Resumption Impact*. In contrast to our baseline findings, the estimated coefficients on this modified measure become statistically insignificant. These results suggest that flows do not respond to firm-specific news of stock holdings if investors cannot observe them when making investment decisions.

2.4.3.2 Unobserved Non-Top-10 Holdings

There is another situation in which a fund might actually hold suspended stocks that can substantially affect future NAV in predictable ways, but the investors are unable to observe these holdings. This possibility arises from the fact that only the top-10 stock

[8] Quarterly portfolio reports are disclosed within 15 business days from the end of each quarter.

holdings are disclosed in fund quarterly reports. Although full disclosures of complete portfolios are available in semi-annual and annual reports, investors can only observe top-10 holdings in timely manner because these two reports are significantly delayed.[9]

The differential timeliness of disclosed top-10 holdings and full portfolios creates an interesting setting for our study. As Table 2.2 shows, for less-diversified funds, stock positions below top-10 holdings can still materially affect the future NAV if the firms experience major news. Because of the long reporting lags, it is unlikely that investors can observe non-top-10 stock holdings of a fund during Q1. Therefore, while fund flows in Q1 might respond to *Resumption Impact* of stocks in top-10 Q4-end disclosure, there should be no response to *Resumption Impact* of non-top-10 Q4-end holdings.

To empirically examine this conjecture, we calculate *Non-top-10 RI* as the *Resumption Impact* of stocks among the non-top-10 holdings of a fund's portfolio disclosed in its annual report. By construction, *Non-top-10 RI* is equal to 0 for fund-quarters not in Q1. We only use non-top-10 holdings in annual reports because the 90-day reporting lag leaves investors no time to respond in the concurrent quarter and provides a clean setting. Table 2.6 reports the results of regressions of fund flows on both *RI* and *Non-top-10 RI*. Column (1) repeats the baseline result for comparison. Column (2) shows that *Non-top-10 RI* does not appear to affect flows, presumably because the relevant holdings are not observable to investors while they make investment decisions in the concurrent quarter. Column (3) and (4) exclude fund-quarter observations with non-zero *RI* in quarters other than Q1, and obtain similar results. Column (5) to (7)

[9]Semi-annual and annual reports have lags of 60 and 90 calendar days, respectively.

use abnormal return as return and performance measures and yield similar results.

In sum, these placebo tests highlight the key role of fund portfolio disclosure in facilitating fund investors' informed investment decisions: trading suspension affects fund flows only when the holdings of suspended stocks are publicly reported.

2.4.4 Do Individual or Institutional Flows Respond More to Resumption Impact?

The prior literature finds that flows from individual investors to mutual funds behave differently from those from institutional investors (Del Guercio and Tkac, 2002, Goyal and Wahal, 2008, Evans and Fahlenbrach, 2012). Institutional investors tend to monitor fund performance more carefully and impose more discipline on the operation of asset managers. We might therefore expect institutional flows to respond more strongly to resumption impacts on funds holding suspended stock becuase they pay closer attention to fund operations.

We examine the potential heterogeneity in responsiveness to resumption impact between individual flows and institutional flows using data on decomposition of fund ownership disclosed in fund semi-annual and annual reports. To compare the flow responses from different investor bases, we create a dummy variable *High Institutional Ratio* that equals to one if the fund has more than 50% assets in the hands of institutional investors according to its disclosure for the most recent half-year-end.[10] We then interact this *High Institutional Ratio* dummy variable with *RI* to augment our baseline specification. Table 2.7 reports the results of this interaction specification. The

[10]The 50% cutoff roughly corresponds to the 80th percentile of the sample.

coefficient of *RI* is positive and significant, confirming that individual flows respond to trading opportunities on suspended stocks held by funds. More interestingly, the coefficient of the interaction term between *RI* and *High Institutional Ratio* is positive and large compare to the baseline coefficient, albeit marginally statistically significant. The evidence is modest but lends some support to the notion that institutional investors pay closer attention to trading opportunities that exploit stale fund NAVs due to suspended stocks in fund portfolios.

2.5 Robustness

We report that our main results are not driven by specific time episodes with volatile markets, and are robust to using different sample and variable filters.

2.5.1 The 2015 Crash Period

In June and July of 2015, the Chinese stock market experienced a dramatic crash. More than a half of all the stocks are in suspension status at the peak of the episode. The focus of our study is not on this period and is broader about the stock and mutual fund markets, though the crash is an important event and has been explored more carefully by other researchers (Huang, Shi, Song, and Zhao (2018), Liu, Xu, and Zhong (2017)). Nonetheless, one may worry that our findings are driven by these crash period observations. To address this, we repeat our baseline regression in Table 2.8 by excluding the observations in the two quarters, 2015Q2 and 2015Q3, surrounding the crash period. When using 5-day post-resumption raw returns as proxy for trading opportunities on suspended stocks, column (1) of Table 2.8 shows that the flow response

to positive opportunities is 1.026, comparable to the baseline estimate 1.059 obtained using the full sample. In column (2), we report the results using the subsample that includes only observations during the crash period, and find positive but statistically insignificant coefficient on *5-day Resumption Impact*. Column (3) and (4) repeat the tests using abnormal returns as stock and fund performance measures, and find similar results. These results verify that our main findings are not driven by extreme events in the stock crash period.

2.5.2 Horizon of Measuring Resumption Impact

For our main specifications, we construct measures of *Resumption Impact* using 5-day stock returns following resumption of trading. We show in Table 2.9 that perturbing this arbitrary choice of return horizon is not crucial for our main findings.

2.5.3 Portfolio Weight in the Construction of Resumption Impact

In the baseline specifications, *Resumption Impact* for fund j in quarter t, $RI_{j,t+1}$, is constructed using 5-day post-resumption returns for suspended holdings during quarter $t+1$, and portfolio weights at the end of quarter $t-1$. We choose to use quarter $t-1$ portfolio weights to reflect investors' information from holdings disclosures they observe during quarter t. However, this may cause inaccuracy in measuring the impact of post-resumption returns of stocks on fund NAVs because the portfolio weights may have changed, due to adjustments of other non-suspended stock positions, from the end of quarter $t-1$ to the resumption dates. To evaluate the impact of this issue, we reconstruct $RI_{j,t+1}$ using portfolio weights at the end of quarter t. Although this information

is not observed by investors at the time flow happens, it presumably gives us a more accurate measure of the impact of stock resumption returns on fund NAVs. We repeat the baseline regression using this modified resumption impact measure, and report the results in Table 2.10. Compared to the baseline results in Table 2.3, using the alternative *Resumption Impact* measure does not introduce material changes to the results, except for slightly increasing the coefficients on *Resumption Impact*.

2.5.4 Extreme Flow Observations

Table 2.11 show that our main results are robust to excluding extreme flow observations at different level. The magnitude of coefficient decreased as we exclude more flow observations at the two tails, but the effect remains statistically strong.

2.5.5 Time Window from Flow Quarter-End to Stock Resumption Date

When calculating *Resumption Impact*, we restrict that the suspended stocks are resumed in the first 2 months (42 trading days) of the next quarter. The purpose is to exclude the stocks that are resumed too distant in the future so that investors in the concurrent quarter are less likely to be confident about the fair value of the stock and act in the mutual fund market accordingly. At the same time, we want to keep as many valid observations as possible. Nonetheless, we show in Table 2.12 that our main results are generally robust to changing this filter to 1 month or removing this filter. As expected, the effect is weakened if the time window filter is removed. Notably, the magnitude of the effect is similar to using a 2-month filter. The statistical significance is lower presumably because less valid observations end up with non-zero *Resumption*

Impact. Overall, this shows that the 2-month filter is an innocuous empirical compromise and our results are not an artifact of sample selection.

2.6 Conclusion

Existing research on financial regulations largely focus on the direct effects of regulatory policies on targeted markets and participants. This study's empirical findings highlight how trading regulations can have unintended consequences in other markets. Trading suspensions prevent stock prices from timely incorporating publicly available information, rendering stock prices stale. Though such stale prices cannot be directly exploited in the stock market, investors can trade mutual funds with stale NAVs due to their inability to adjust for values of holdings of suspended stocks. We show that money flows positively respond to unrealized impact on fund NAVs for mutual funds that hold stocks that experience trading suspensions. These opportunistic investor flows tend to dilute future fund profits and concentrate future fund losses, imposing externalities on long-term fund investors. Thus, the welfare of investors are affected by the trading regulations beyond investors in the stock markets. Our findings prompt policy makers to consider spillover effects of financial regulations as financial markets become increasingly complex.

Tables and Figures

Table 2.1: Correlation Between Stock Return on Fund NAV Return Following Resumption

Panel A: Raw Return					
correlation between		if |portfolio weight × 5-day return|			
portfolio weight × post-resumption return	fund return after resumption	all	> 1%	> 3%	> 5%
1 day	1 day	0.047	0.127	0.257	0.458
3 days	3 days	0.114	0.247	0.321	0.344
5 days	5 days	0.163	0.300	0.428	0.445
7 days	7 days	0.159	0.337	0.486	0.583
10 days	10 days	0.244	0.336	0.465	0.576
15 days	15 days	0.310	0.376	0.478	0.522
# events		16,556	3,205	362	64

Panel B: Abnormal Return					
correlation between		if |portfolio weight × 5-day return|			
portfolio weight × post-resumption return	fund return after resumption	all	> 1%	> 3%	> 5%
1 day	1 day	0.115	0.172	0.442	0.632
3 days	3 days	0.119	0.164	0.260	0.384
5 days	5 days	0.157	0.239	0.367	0.438
7 days	7 days	0.194	0.269	0.397	0.525
10 days	10 days	0.192	0.254	0.363	0.467
15 days	15 days	0.218	0.273	0.382	0.403
# events		16,556	3,205	362	64

Table 2.2: Summary Statistics

This table reports summary statistics of fund characteristics. Only non-structured open-end mutual funds are included in the sample. The unit of observation is fund-quarter where a fund files a quarterly report. Fund flows and returns are calculated for quarterly intervals. Fund TNA is reported in million CNY. Fund ages are reported in number of years. Fund flows are trimmed at the 1% and 99% levels.

Panel A: All Fund-Quarters										
Varaible	N	Mean	Std	p1	p10	p25	Median	p75	p90	p99
Fund Flow	26,221	-3.47%	23.98%	-53.77%	-23.54%	-10.94%	-3.95%	-0.29%	10.37%	99.88%
Raw Return										
Fund Performance	26,221	2.69%	12.09%	-27.16%	-9.84%	-2.74%	1.39%	6.72%	17.31%	41.12%
Family Performance	26,170	2.05%	9.36%	-20.96%	-7.87%	-2.16%	1.22%	4.97%	14.14%	30.87%
Abnormal Return										
Fund Performance	25,926	1.51%	8.21%	-21.56%	-5.77%	-1.73%	0.74%	4.02%	9.26%	32.37%
Family Performance	25,875	0.90%	5.60%	-17.56%	-3.47%	-1.24%	0.37%	2.63%	6.18%	20.59%
Fund TNA	26,228	2,198	3,569	54	106	266	931	2,593	5,762	16,641
Fund Age	26,228	4.97	3.19	1.28	1.62	2.33	4.08	6.93	9.78	13.89
Fund Return Volatility	26,219	5.68%	3.89%	0.25%	0.93%	2.90%	4.97%	7.85%	11.21%	17.00%
Family TNA	26,228	36,133	35,700	514	4,543	10,325	24,581	48,069	85,114	151,947
Purchase Fee	26,108	0.01%	0.07%	0.00%	0.00%	0.00%	0.01%	0.02%	0.02%	0.02%
Redemption Fee	26,039	0.03%	0.11%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.50%
Expense Ratio	26,223	1.54%	0.42%	0.20%	0.80%	1.50%	1.75%	1.75%	1.75%	2.15%
No. Funds	1,837									
No. Families	107									

Panel B: Event Fund-Quarters

Varaible	N	Mean	Std	p1	p10	p25	Median	p75	p90	p99
Fund Flow	4,588	-4.94%	24.77%	-54.09%	-27.67%	-13.57%	-5.12%	-1.03%	10.68%	101.91%
Raw Return										
RI(3d)	4,497	0.05%	1.11%	-2.92%	-1.10%	-0.46%	0.03%	0.52%	1.22%	3.54%
RI(5d)	4,497	0.04%	1.45%	-3.83%	-1.31%	-0.57%	-0.02%	0.52%	1.41%	4.88%
RI(7d)	4,497	0.07%	1.72%	-4.14%	-1.40%	-0.61%	-0.04%	0.54%	1.54%	6.33%
RI(10d)	4,497	0.08%	1.92%	-4.58%	-1.42%	-0.65%	-0.08%	0.49%	1.60%	7.12%
Fund Performance	4,588	4.62%	14.61%	-30.51%	-11.45%	-2.92%	2.83%	11.52%	24.17%	45.72%
Family Performance	4,583	3.50%	10.29%	-21.41%	-8.06%	-1.40%	2.19%	9.01%	17.02%	32.61%
Abnormal Return										
RI(3d)	4,539	-0.01%	1.08%	-3.23%	-1.15%	-0.49%	0.04%	0.47%	1.08%	2.96%
RI(5d)	4,539	-0.09%	1.38%	-4.25%	-1.48%	-0.64%	-0.03%	0.46%	1.21%	3.81%
RI(7d)	4,539	-0.10%	1.57%	-4.94%	-1.56%	-0.69%	-0.06%	0.46%	1.28%	4.71%
RI(10d)	4,539	-0.13%	1.71%	-5.13%	-1.62%	-0.71%	-0.11%	0.43%	1.32%	5.10%
Fund Performance	4,506	2.54%	11.91%	-31.40%	-8.51%	-2.78%	1.55%	6.88%	15.92%	40.91%
Family Performance	4,501	1.41%	7.38%	-23.20%	-4.56%	-1.28%	0.85%	4.04%	9.63%	24.30%
Fund TNA	4,588	1,926	2,775	54	107	270	934	2,442	4,868	13,057
Fund Age	4,588	5.48	3.32	1.28	1.75	2.62	4.76	7.91	10.45	13.60
Fund Return Volatility	4,588	7.30%	4.22%	0.97%	2.89%	4.02%	6.05%	10.24%	13.58%	18.64%
Family TNA	4,588	33,506	33,583	376	3,716	9,130	22,878	44,380	79,264	146,585
Purchase Fee	4,583	0.02%	0.08%	0.00%	0.00%	0.00%	0.01%	0.02%	0.02%	0.10%
Redemption Fee	4,570	0.03%	0.12%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.50%
Expense Ratio	4,588	1.69%	0.24%	0.25%	1.75%	1.75%	1.75%	1.75%	1.75%	1.75%
No. Funds	985									
No. Families	92									

Panel C: Top-10 Holding Positions										
Rank of Holding	N	Mean	Std	p1	p10	p25	Median	p75	p90	p99
1	23,697	5.69%	2.68%	0.06%	1.79%	4.00%	5.69%	7.72%	9.25%	10.63%
2	23,453	4.75%	2.31%	0.04%	1.42%	3.28%	4.78%	6.21%	7.91%	9.71%
3	23,280	4.18%	2.06%	0.03%	1.22%	2.95%	4.19%	5.40%	6.88%	9.27%
4	23,113	3.77%	1.86%	0.03%	1.11%	2.69%	3.78%	4.90%	6.07%	8.73%
5	22,976	3.45%	1.68%	0.02%	1.04%	2.48%	3.45%	4.49%	5.43%	7.98%
6	22,822	3.18%	1.53%	0.02%	0.98%	2.30%	3.18%	4.12%	5.00%	7.28%
7	22,695	2.95%	1.39%	0.01%	0.94%	2.16%	2.99%	3.82%	4.64%	6.54%
8	22,560	2.75%	1.28%	0.01%	0.89%	2.05%	2.83%	3.54%	4.27%	5.86%
9	22,440	2.58%	1.17%	0.01%	0.86%	1.96%	2.66%	3.29%	3.99%	5.31%
10	22,333	2.42%	1.08%	0.01%	0.82%	1.86%	2.50%	3.08%	3.70%	4.92%
Average	23,697	3.52%	1.64%	0.03%	1.01%	2.59%	3.63%	4.61%	5.52%	7.18%
Sum	23,697	34.75%	16.78%	0.15%	8.38%	25.17%	36.14%	45.97%	55.07%	71.48%

Table 2.3: Baseline Regression

This table reports results in baseline specification. The dependent variable is quarterly fund flow, and observations are at fund-quarter level. The variable of interest, *Resumption Impact (5d)*, is holding-weighted sum of 5-trading day post-resumption stock return, calculated based on disclosed top-10 fund portfolio holdings at the quarter end prior to the reference date. In the first two columns, *Resumption Impact (5d)*, *Fund Performance* and *Family Performance* are measured using raw returns. In columns (3)-(4), *Resumption Impact (5d)* is measured using stock-market adjusted abnormal return, and *Fund Performance* and *Family Performance* are measured using stock- and bond-market adjusted abnormal return. The fund itself is excluded when calculating family TNA and performance. All control variables are lagged by one quarter. Standard errors are clustered at fund level, and t-statistics are reported in parentheses. *, **, *** represent 10%, 5%, and 1% level of significance.

	Raw Return		Abnormal Return	
	(1)	(2)	(3)	(4)
Resumption Impact (5d)	1.097***	1.059***	1.205***	1.120***
	(3.575)	(3.585)	(3.858)	(3.703)
Fund Performance	0.327***	0.343***	0.405***	0.426***
	(8.380)	(8.590)	(11.946)	(12.713)
Log TNA		-0.071***		-0.072***
		(-14.425)		(-14.244)
Log Age		-0.003		-0.001
		(-0.358)		(-0.094)
Log Familiy TNA		0.013**		0.014***
		(2.447)		(2.606)
Family Performance		0.219***		0.113*
		(3.738)		(1.852)
Fund Return Volatility		-0.178*		-0.417***
		(-1.655)		(-3.918)
Purchase Fee		-4.702*		-7.356*
		(-1.666)		(-1.929)
Redemption Fee		12.560		3.674
		(0.822)		(0.170)
Expense Ratio		1.757		2.152
		(0.246)		(0.300)
Fund FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
Observations	26,052	25,776	25,757	25,493
R-squared	0.130	0.155	0.132	0.158

Table 2.4: Interaction Specification

This table reports results of modified baseline regressions that include interaction terms. The dependent variable is quarterly fund flow, and observations are at fund-quarter level. Variable *Resumption Impact (5d)*, or $RI(5d)$, is holding-weighted sum of 5-trading day post-resumption stock return, calculated based on disclosed top-10 fund portfolio holdings at the quarter end prior to the reference date. $\mathbf{1}_{RI(5d)>0}$ is an indicator variable that equals one if *Resumption Impact (5d)* is positive. *Left Tail* and *Right Tail* are indicator variables that equal one if $|RI(5d)| > 3\%$ on the corresponding tail of distribution. In Panel A, *RI(5d)*, *Fund Performance* and *Family Performance* are measured using raw returns. In Panel B, *RI(5d)* is measured using stock-market adjusted abnormal return, and *Fund Performance* and *Family Performance* are measured using stock- and bond-market adjusted abnormal return. The fund itself is excluded when calculating family TNA and performance. All control variables are lagged by one quarter. Standard errors are clustered at fund level, and t-statistics are reported in parentheses. *, **, *** represent 10%, 5%, and 1% level of significance.

	Panel A: Raw Return					
	(1)	(2)	(3)	(4)	(5)	(6)
RI (5d)	1.216***	1.323***	0.952**	0.887**	1.068***	1.082***
	(2.861)	(3.145)	(2.573)	(2.486)	(2.828)	(2.936)
Positive	-0.012*	-0.013*				
	(-1.769)	(-1.838)				
RI (5d) * Positive	0.235	-0.000				
	(0.331)	(-0.000)				
Left Tail			-0.107*	-0.094		
			(-1.870)	(-1.623)		
RI (5d) * Left Tail			-1.534	-1.127		
			(-1.386)	(-0.993)		
Right Tail					-0.215***	-0.192***
					(-3.667)	(-3.440)
RI (5d) * Right Tail					3.864***	3.332***
					(2.883)	(2.641)
Control Variables	No	Yes	No	Yes	No	Yes
Fund FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,052	25,776	26,052	25,776	26,052	25,776
R-squared	0.130	0.156	0.130	0.156	0.130	0.156

	Panel B: Abnormal Return					
	(7)	(8)	(9)	(10)	(11)	(12)
RI (5d)	1.042***	1.051***	1.409***	1.311***	0.966***	0.949***
	(2.646)	(2.694)	(3.673)	(3.553)	(2.834)	(2.846)
Positive	-0.013*	-0.013*				
	(-1.841)	(-1.886)				
RI (5d) * Positive	0.955	0.748				
	(1.212)	(0.990)				
Left Tail			0.113	0.119		
			(1.115)	(1.167)		
RI (5d) * Left Tail			1.561	1.715		
			(0.952)	(1.045)		
Right Tail					-0.297***	-0.288***
					(-3.764)	(-3.962)
RI (5d) * Right Tail					6.800***	6.350***
					(3.492)	(3.569)
Control Variables	No	Yes	No	Yes	No	Yes
Fund FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,757	25,493	25,757	25,493	25,757	25,493
R-squared	0.132	0.158	0.132	0.158	0.133	0.158

Table 2.5: Placebo Test: Unobserved Actual Top-10 Holdings

This table reports results of placebo tests based on actual top-10 fund holdings that are unobservable to investors. The dependent variable is quarterly fund flow, and observations are at fund-quarter level. The variable of interest, *Resumption Impact (5d)*, is holding-weighted sum of 5-trading day post-resumption stock return, calculated based on disclosed top-10 fund portfolio holdings that appear at the end of the concurrent quarter, but not the end of the previous quarter. In the first two columns, *Resumption Impact (5d)*, *Fund Performance* and *Family Performance* are measured using raw returns. In columns (3)-(4), *Resumption Impact (5d)* is measured using stock-market adjusted abnormal return, and *Fund Performance* and *Family Performance* are measured using stock- and bond-market adjusted abnormal return. The fund itself is excluded when calculating family TNA and performance. All control variables are lagged by one quarter. Standard errors are clustered at fund level, and t-statistics are reported in parentheses. *, **, *** represent 10%, 5%, and 1% level of significance.

	Raw Return		Abnormal Return	
	(1)	(2)	(3)	(4)
Resumption Impact (5d)	-0.649	-0.783	0.182	-0.028
	(-1.097)	(-1.389)	(0.321)	(-0.053)
Fund Performance	0.322***	0.338***	0.397***	0.418***
	(8.250)	(8.467)	(11.602)	(12.434)
Log TNA		-0.071***		-0.072***
		(-14.410)		(-14.227)
Log Age		-0.003		-0.001
		(-0.365)		(-0.092)
Log Family TNA		0.013**		0.014**
		(2.409)		(2.557)
Family Performance		0.216***		0.111*
		(3.685)		(1.811)
Fund Return Volatility		-0.192*		-0.425***
		(-1.778)		(-3.981)
Purchase Fee		-4.842*		-7.599**
		(-1.723)		(-2.012)
Redemption Fee		12.608		3.670
		(0.838)		(0.173)
Expense Ratio		1.732		2.061
		(0.242)		(0.287)
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	26,052	25,776	25,757	25,493
R-squared	0.129	0.155	0.131	0.157

Table 2.6: Placebo Test: Unobserved Non-Top-10 Holdings

This table reports results of placebo tests exploiting the delay of fund disclosure of non-top-10 stock holdings in annual reports. The dependent variable is quarterly fund flow. *RI(5d)* is the 5-day Resumption Impact calculated using the top-10 holdings. *Non-top-10 RI(5d)* is the 5-day Resumption Impact calculated using the non-top-10 holdings disclosed in fund annual reports. Column (1)-(4) measure stock and fund performance using raw return, and column (5)-(8) use abnormal return. Column (1), (2), (5), and (6) include all fund-quarter observations in the baseline sample, while column (3), (4), (7), and (8) exclude fund-quarter observations where *RI(5d)* is non-zero and the quarter is not Q1. All control variables are lagged by one quarter. Standard errors are clustered at fund level, and t-statistics are reported in parentheses. *, **, *** represent 10%, 5%, and 1% level of significance.

	Raw Return				Abnormal Return			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RI (5d)	1.059***	1.069***	1.325**	1.356**	1.120***	1.114***	1.468**	1.451**
	(3.585)	(3.626)	(2.266)	(2.338)	(3.703)	(3.692)	(2.257)	(2.246)
Non-top-10 RI (5d)		-0.501		-0.580		0.547		0.474
		(-0.483)		(-0.560)		(0.442)		(0.381)
Fund Performance	0.343***	0.343***	0.316***	0.316***	0.426***	0.427***	0.408***	0.409***
	(8.590)	(8.542)	(7.313)	(7.275)	(12.713)	(12.664)	(11.178)	(11.134)
Log TNA	-0.071***	-0.071***	-0.068***	-0.068***	-0.072***	-0.072***	-0.069***	-0.069***
	(-14.425)	(-14.425)	(-13.220)	(-13.220)	(-14.244)	(-14.244)	(-13.156)	(-13.155)
Log Age	-0.003	-0.003	-0.007	-0.007	-0.001	-0.001	-0.005	-0.005
	(-0.358)	(-0.354)	(-0.726)	(-0.721)	(-0.094)	(-0.098)	(-0.481)	(-0.484)
Log Family TNA	0.013**	0.013**	0.012**	0.012**	0.014***	0.014***	0.013**	0.013**
	(2.447)	(2.446)	(2.231)	(2.230)	(2.606)	(2.607)	(2.383)	(2.384)
Family Performance	0.219***	0.219***	0.171***	0.171***	0.113*	0.113*	0.033	0.033
	(3.738)	(3.738)	(2.718)	(2.718)	(1.852)	(1.847)	(0.510)	(0.505)
Fund Return Volatility	-0.178*	-0.180*	-0.145	-0.148	-0.417***	-0.415***	-0.384***	-0.382***
	(-1.655)	(-1.669)	(-1.240)	(-1.259)	(-3.918)	(-3.893)	(-3.324)	(-3.306)
Purchase Fee	-4.702*	-4.708*	-3.533	-3.540	-7.356*	-7.343*	-4.756	-4.747
	(-1.666)	(-1.669)	(-1.197)	(-1.200)	(-1.929)	(-1.923)	(-1.051)	(-1.048)
Redemption Fee	12.560	12.484	9.955	9.856	3.674	3.784	0.933	1.042
	(0.822)	(0.817)	(0.606)	(0.601)	(0.170)	(0.175)	(0.044)	(0.049)
Expense Ratio	1.757	1.748	4.936	4.925	2.152	2.164	5.380	5.390
	(0.246)	(0.245)	(0.649)	(0.647)	(0.300)	(0.301)	(0.706)	(0.708)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,776	25,776	22,565	22,565	25,493	25,493	22,362	22,362
R-squared	0.155	0.155	0.162	0.162	0.158	0.158	0.165	0.165

Table 2.7: Flow Response for Funds with Different Institutional Ratios

This table reports results on the heterogeneous responsiveness of individual flows and institutional flows to *Resumption Impact*. *High Institutional Ratio* is a dummy variable that equals to 1 if the fund ownership by institutional investors is above 50% according to the most recent disclosure, and 0 otherwise. Definition of other variables are the same as in the baseline specification. Standard errors are clustered at fund level, and t-statistics are reported in parentheses. *, **, *** represent 10%, 5%, and 1% level of significance.

	Raw Return		Abnormal Return	
	(1)	(2)	(3)	(4)
RI	0.815**	0.788**	0.875**	0.808**
	(2.374)	(2.351)	(2.482)	(2.343)
RI × High Inst. Ratio	1.492*	1.317*	1.705**	1.576**
	(1.934)	(1.816)	(2.107)	(2.043)
Fund Performance	0.308***	0.326***	0.394***	0.413***
	(7.844)	(8.136)	(11.200)	(11.967)
Fund Perf. × High Inst. Ratio	0.123**	0.096*	0.064	0.076
	(2.378)	(1.878)	(0.892)	(1.089)
High Institutional Ratio	-0.053***	-0.026***	-0.048***	-0.023***
	(-6.766)	(-3.197)	(-5.868)	(-2.632)
Log TNA		-0.068***		-0.070***
		(-13.755)		(-13.564)
Log Age		-0.004		-0.001
		(-0.380)		(-0.130)
Log Familiy TNA		0.013**		0.014**
		(2.366)		(2.571)
Family Performance		0.215***		0.109*
		(3.669)		(1.781)
Fund Return Volatility		-0.216**		-0.449***
		(-2.023)		(-4.237)
Purchase Fee		-4.588*		-7.251*
		(-1.695)		(-1.898)
Redemption Fee		10.530		1.600
		(0.707)		(0.075)
Expense Ratio		2.078		2.453
		(0.292)		(0.342)
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	26,052	25,776	25,757	25,493
R-squared	0.133	0.156	0.135	0.158

Table 2.8: The 2015 Market Crash Period

This table shows results of the baseline regression using the sample excluding the 2015 market crash period observations. Crash period observations are fund-quarters observed in 2015Q2 or 2015Q3. The dependent variable is quarterly fund flow. Column (1) and (3) use non-crash-period observations, and column (2) and (4) use only crash-period observations. Standard errors are clustered at fund level, and t-statistics are reported in parentheses. *, **, *** denote 10%, 5%, and 1% level of significance.

	Raw Return		Abnormal Return	
	(1)	(2)	(3)	(4)
Resumption Impact (5d)	1.026***	0.825	1.140***	0.649
	(2.909)	(1.288)	(3.236)	(0.943)
Fund Performance	0.364***	0.409***	0.440***	0.528***
	(8.471)	(3.697)	(12.553)	(4.295)
Log TNA	-0.067***	-0.026***	-0.068***	-0.029***
	(-14.171)	(-3.127)	(-13.955)	(-3.582)
Log Age	0.005	-0.068***	0.007	-0.062***
	(0.524)	(-4.037)	(0.733)	(-3.680)
Log Family TNA	0.012**	0.006	0.013**	0.007
	(2.280)	(0.557)	(2.469)	(0.619)
Family Performance	0.157**	0.483***	0.014	0.650***
	(2.384)	(2.746)	(0.217)	(2.614)
Fund Return Volatility	-0.216**	-0.916***	-0.482***	-0.739**
	(-2.033)	(-2.857)	(-4.543)	(-2.427)
Purchase Fee	-4.665*	-99.646*	-7.144*	-101.260*
	(-1.649)	(-1.722)	(-1.866)	(-1.761)
Redemption Fee	12.076	4.550	2.866	3.730
	(0.764)	(0.514)	(0.131)	(0.429)
Expense Ratio	1.197	0.387	1.618	-0.355
	(0.171)	(0.157)	(0.231)	(-0.140)
Fund FE	Yes	No	Yes	No
Time FE	Yes	Yes	Yes	Yes
Observations	24,380	1,395	24,097	1,395
R-squared	0.159	0.081	0.161	0.085

Table 2.9: Robustness: Horizon of Measuring Resumption Impact

This table shows that our main results are robust to constructing our variable of interest *Resumption Impact* using stock resumption returns over various lengths of time. Column (1), (3), and (5) measures stock and fund performance using raw return, and column (2), (4), (6) uses abnormal return adjusted for exposure to stock and bond market factors. All control variables in the baseline specification are included and their coefficients are suppressed to conserve space. Standard errors are clustered at fund level, and t-statistics are reported in parentheses. *, **, *** denote 10%, 5%, and 1% level of significance.

	n=3		n=7		n=10	
	(1)	(2)	(3)	(4)	(5)	(6)
Resumption Impact (n days)	1.233***	1.343***	1.012***	1.183***	0.914***	1.012***
	(3.372)	(3.631)	(3.910)	(4.436)	(3.735)	(4.002)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,776	25,493	25,776	25,493	25,776	25,493
R-squared	0.155	0.157	0.156	0.158	0.156	0.158

Table 2.10: : Robustness: Using More Accurate Portfolio Weight to Construct Resumption Impact

This table reports results for the baseline regression using modified resumption impact measure. The dependent variable is quarterly fund flow, and observations are at fund-quarter level. The variable of interest, *Resumption Impact (5d)*, is holding-weighted sum of 5-trading day post-resumption stock return, calculated based on disclosed top-10 fund portfolio holdings at the quarter end prior to the reference date. In the first two columns, *Resumption Impact (5d)*, *Fund Performance* and *Family Performance* are measured using raw returns. In columns (3)-(4), *Resumption Impact (5d)* is measured using stock-market adjusted abnormal return, and *Fund Performance* and *Family Performance* are measured using stock- and bond-market adjusted abnormal return. The fund itself is excluded when calculating family TNA and performance. All control variables are lagged by one quarter. Standard errors are clustered at fund level, and t-statistics are reported in parentheses. *, **, *** represent 10%, 5%, and 1% level of significance.

	Raw Return		Abnormal Return	
	(1)	(2)	(3)	(4)
Resumption Impact (5d)	1.285***	1.261***	1.333***	1.269***
	(3.736)	(3.842)	(3.905)	(3.869)
Fund Performance	0.328***	0.344***	0.405***	0.426***
	(8.381)	(8.593)	(11.935)	(12.714)
Log TNA		-0.071***		-0.072***
		(-14.433)		(-14.252)
Log Age		-0.003		-0.001
		(-0.353)		(-0.094)
Log Familiy TNA		0.013**		0.014***
		(2.447)		(2.606)
Family Performance		0.219***		0.113*
		(3.742)		(1.853)
Fund Return Vol		-0.177*		-0.416***
		(-1.647)		(-3.915)
Purchase Fee		-4.676*		-7.331*
		(-1.654)		(-1.920)
Redemption Fee		12.618		3.758
		(0.824)		(0.174)
Expense Ratio		1.742		2.158
		(0.244)		(0.300)
Fund FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes
Observations	26,052	25,776	25,757	25,493
R-squared	0.130	0.156	0.132	0.158

Table 2.11: Robustness: Trimming Extreme Flow Observations

This table shows that our main results are robust to excluding fund-quarter observations where funds experience extreme flows. Column (1) and (3) use raw return to measure stock return and fund performance, while column (2) and (4) use abnormal return adjusted for exposure to stock and bond market factors. Standard errors are clustered at fund level, and t-statistics are reported in parentheses. *, **, *** denote 10%, 5%, and 1% level of significance.

	Trim at (2.5%, 97.5%)		Trim at (5%, 95%)	
	(1)	(2)	(3)	(4)
Resumption Impact (5d)	0.894***	1.023***	0.735***	0.818***
	(3.937)	(4.534)	(4.607)	(5.115)
Fund Performance	0.210***	0.268***	0.125***	0.161***
	(8.933)	(12.592)	(7.838)	(10.300)
Log TNA	-0.035***	-0.036***	-0.021***	-0.021***
	(-12.948)	(-12.722)	(-10.497)	(-10.257)
Log Age	0.003	0.004	0.005	0.006
	(0.472)	(0.714)	(1.105)	(1.338)
Log Family TNA	0.007**	0.008**	0.005**	0.006***
	(2.283)	(2.455)	(2.534)	(2.631)
Family Performance	0.110***	0.055	0.073***	0.051*
	(2.988)	(1.359)	(2.862)	(1.762)
Fund Return Volatility	0.004	-0.142**	0.130**	0.043
	(0.057)	(-2.044)	(2.566)	(0.849)
Purchase Fee	-3.566**	-4.804**	-2.929**	-5.251**
	(-1.977)	(-2.043)	(-2.290)	(-2.294)
Redemption Fee	5.734	0.975	5.632	5.608
	(0.649)	(0.081)	(1.276)	(0.857)
Expense Ratio	-1.372	-1.029	-1.423	-1.176
	(-0.398)	(-0.298)	(-0.461)	(-0.378)
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	24,978	24,695	23,649	23,376
R-squared	0.182	0.185	0.209	0.213

Table 2.12: Robustness: Time Window from Flow Quarter-End to Stock Resumption Date

This table shows robustness of our main results to varying time window applied to filter stock resumption events used to calculate *Resumption Impact*. Column (1) and (3) use raw return to measure stock return and fund performance, Column (2) and (4) use abnormal returns. Standard errors are clustered at fund level, and t-statistics are reported in parentheses. *, **, *** denote 10%, 5%, and 1% level of significance.

	w=1 month		w=3 months	
	(1)	(2)	(3)	(4)
Resumption Impact (5d)	1.060***	1.096***	0.629**	0.582*
	(2.990)	(2.894)	(2.143)	(1.916)
Fund Performance	0.343***	0.424***	0.341***	0.422***
	(8.581)	(12.685)	(8.534)	(12.602)
Log TNA	-0.071***	-0.072***	-0.071***	-0.072***
	(-14.416)	(-14.237)	(-14.417)	(-14.234)
Log Age	-0.003	-0.001	-0.003	-0.001
	(-0.368)	(-0.101)	(-0.356)	(-0.091)
Log Family TNA	0.013**	0.014***	0.013**	0.014***
	(2.437)	(2.595)	(2.425)	(2.580)
Log Family Performance	0.219***	0.114*	0.219***	0.112*
	(3.736)	(1.862)	(3.735)	(1.834)
Fund Return Volatility	-0.177*	-0.416***	-0.182*	-0.419***
	(-1.646)	(-3.907)	(-1.686)	(-3.941)
Purchase Fee	-4.693*	-7.346*	-4.729*	-7.449*
	(-1.665)	(-1.930)	(-1.681)	(-1.954)
Redemption Fee	12.568	3.749	12.652	3.792
	(0.826)	(0.175)	(0.839)	(0.178)
Expense Ratio	1.781	2.161	1.712	2.091
	(0.249)	(0.301)	(0.240)	(0.291)
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	25,776	25,493	25,776	25,493
R-squared	0.155	0.157	0.155	0.157

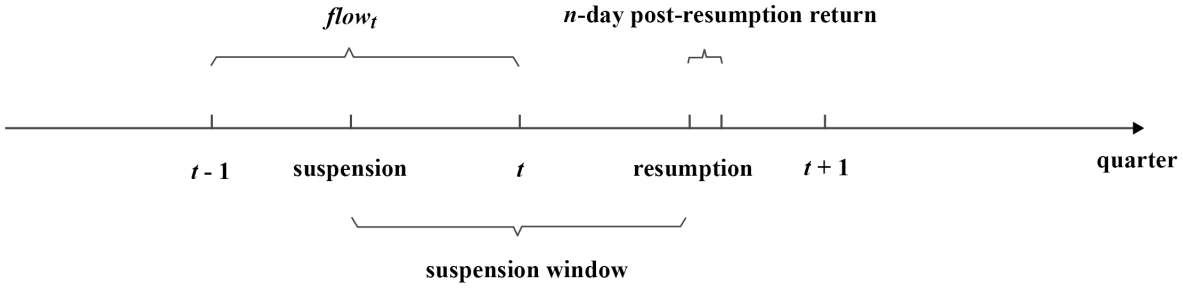
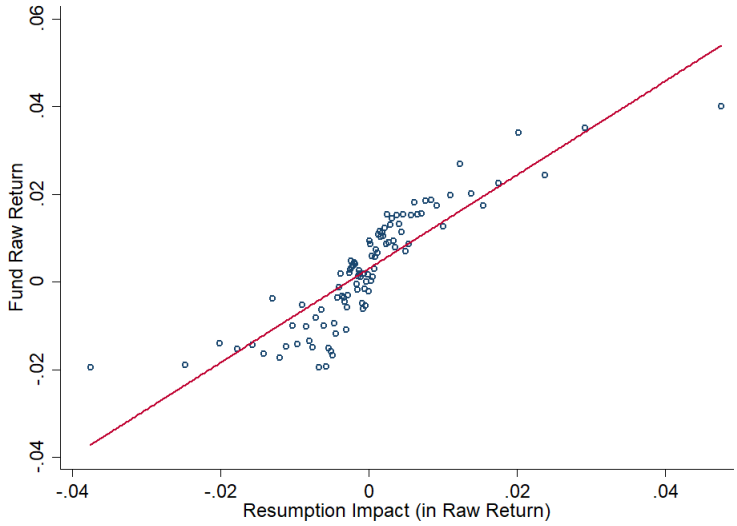


Figure 2.1: Timeline.



(a) 5-day raw returns following resumption

(b) 5-day abnormal returns following resumption

Figure 2.2: Binscatter plot of mutual fund return and resumption impact over 5 trading days following stock resumption

Plot for all trading suspension events with at least 1% portfolio weight during 2004Q3-2018Q2. Events are grouped into 100 bins. For each fund-stock event in this dataset, trading suspension is required to occur before the reference date, so the fund holds the corresponding stock for sure.

Appendix

A.1 Supplement Thomson Holdings Data Using CRSP Holdings Data

The study presented in Chapter 1 utilizes mutual fund holdings data from both CRSP and Thomson Financial databases. As researchers have previously pointed out, the coverage of Thomson Financial holdings data suffers from quality issues noticeably since 2008 (Shive and Yun, 2013; Zhu, 2019). To obtain a more comprehensive coverage for a longer sample period, I supplement Thomson holdings data using CRSP holdings data. CRSP starts to include fund holdings data since 2003. For the entire sample period used in this study, I find 1,160 active U.S. equity mutual funds that have no holdings data in Thomson but are included in CRSP holdings data. These funds either do not exist in the Thomson holdings database, or are not picked up by the MFLINKS link table that is used to link CRSP to Thomson.

In Table A.1, we can observe that there are some big time gaps between the dates of the first reported holdings data in CRSP and fund inception dates for the 1,160 funds. These are mostly due to funds that were started earlier before 2003 when CRSP holdings data begin. Additional reporting gaps are due to limited coverage of CRSP holdings data before 2008. The lackluster quality of CRSP holdings data until 2008 is also noted by Shive and Yun (2013), Schwarz and Potter (2016), and Zhu (2019). Despite the limitations of earlier periods of CRSP coverage, I find 466 entrant funds that has holdings reported in CRSP within the first 12 months following their inception dates but are missing from the Thomson database. Table A.2 details the distribution of these entrants over time. Note that the numbers pike around 2008, consistent with findings by previously mentioned researchers that CRSP has improved quality from 2008

while Thomson started to suffer from quality issues.

A.2 Additional Empirical Results for Chapter 1

A.2.1 Empirical Tests for Performance Differences Between Hot and Cold Style Entrant Funds Using the 1982–2015 Full Sample

This section present additional results of the main empirical tests for Chapter 1 using the full 1982–2015 sample. This sample includes 2,927 entrant funds, compared to 2,801 for the 1991–2015 subsample. Table A.3 reports the t-tests for performance differences between hot and cold entrant funds of different style categories. Tables A.4 and A.5 present the results of the regression tests using the full sample. The results show that including the additional 126 entrant funds does not have any big influence on the main results and conclusions. In addition, Tables A.6 and A.7 replicate the tests in Section 1.4.2 that examine the performance of entrant funds relative to incumbent funds. These tests are particularly important for the contribution of the study as they distinguish the mechanism of entry threshold from alternative explanations such as stock-level return reversal and fund competition effects. As the tables show, the results of these tests in the full sample are similar to those for the 1991–2015 subsample.

A.2.2 Regression Tests with Different Clustering Methods

Tables A.8 and A.9 report t-statistics when different clustering methods are used to compute standard errors for the main regression tests presented in Tables 1.3 and 1.4 in Section 1.4.1.2. For all regression specifications, style fixed effects are included. The baseline calculates t-statistics with standard errors clustered by style-year groups. For comparison, t-statistics are also calculated using robust standard errors, standard

errors clustered by fund vintage year groups, and standard errors clustered by style groups. The robust standard errors do not take into account the correlation among residuals and likely exaggerates the statistical significance of the coefficients. Clustering by style groups results in higher t-statistics in some cases and lower in others, compared to the baseline. Clustering by year groups weakens the statistical significance in all cases. While it is reasonable to consider fund managers' abilities to generate superior performance are correlated for funds in the same style category and for the same point of time, the main concern of using either year and style as cluster is that there are not enough number of clusters for group-level asymptotic to work well. Since there are only 25 year groups and 9 style groups, the paucity of clusters may lead to biased standard errors (Angrist and Pischke, 2008). The choice of using style-year group cluster allows for meaningful correlation among observations, i.e., the abilities of funds that are opened in the same year with same investment style may be correlated, while also provides enough number of cluster groups to ensure reliable estimation. In addition, the results in Table A.9 show that the regressions using past style performance as independent variable yield statistically significant coefficients consistently across different standard error calculation methods. This also lends confidence to the main findings of the study.

Tables and Figures

Table A.1: Number of Months Between Fund Inception Date and the First Holdings Report Date in CRSP Holdings Data

Only actively managed U.S. equity funds that have holdings coverage in CRSP but not in Thomson are included.

N	Min	10th Pctl	25th Pctl	50th Pctl	75th Pctl	90th Pctl	Max
1,160	0	1	3	61	145	197	481

Table A.2: Number of Entrant Funds that Have Holdings Coverage in CRSP But Not in Thomson

This table details the number of entrant funds in CRSP that have missing holdings data in Thomson but can be matched to CRSP holdings data.

Year	#Entrants
2003	2
2004	3
2005	10
2006	3
2007	31
2008	57
2009	61
2010	101
2011	74
2012	84
2013	26
2014	7
2015	7
Total	466

Table A.3: Comparing Post-Entry Performance of Hot and Cold Style Entrant Funds (1982–2015)

An investment style is considered as in hot status if the TNA-weighted average returns of funds in the style category minus the value-weighted CRSP index return in the previous 24 months is above the time-series median of the entire sample. An entrant fund is considered as a hot style entrant fund if its initial holding-based style at the time of its entry is in hot status. Post-entry performance is measured over the 36-month window after the month of the funds' inception date. If the fund is closed within the 36 months, it is still included in the calculation. Return in excess of MKT is measured as the average fund monthly return over the value-weighted CRSP index return. t-statistics of two sample mean tests are reported for the difference between average performance of hot and cold style entrant funds. The sample period is 1982–2015.

		Small			Mid			Large		
	All	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
Panel A: Number of Entrants										
Hot	1,519	363	161	168	161	151	155	60	114	186
Cold	1,408	243	150	119	169	145	115	54	208	205
Total	2,927	606	311	287	330	296	270	114	322	391
Panel B: Return in Excess of MKT										
Hot	-0.039	0.021	0.078	0.117	-0.130	-0.093	0.040	-0.280	-0.196	-0.165
Cold	0.005	0.286	0.047	-0.021	-0.054	0.068	0.037	-0.094	-0.155	-0.172
Difference	-0.043	-0.265	0.032	0.138	-0.076	-0.161	0.002	-0.186	-0.041	0.007
t-stat	-1.741	-3.918	0.385	1.342	-1.225	-2.288	0.030	-1.971	-0.718	0.157

(continued)

		Small			Mid			Large		
	All	Growth	Blend	Value	Growth	Blend	Value	Growth	Blend	Value
Panel C: CAPM Alpha										
Hot	-0.046	-0.020	0.010	0.038	-0.146	-0.065	0.049	-0.227	-0.124	-0.093
Cold	0.040	0.322	0.040	0.045	-0.024	0.111	0.050	-0.099	-0.098	-0.125
Difference	-0.086	-0.342	-0.030	-0.007	-0.122	-0.176	-0.001	-0.128	-0.026	0.032
t-stat	-3.702	-4.933	-0.400	-0.073	-2.066	-2.682	-0.022	-1.705	-0.569	0.849
Panel D: Fama-French 3-Factor Alpha										
Hot	-0.044	0.061	-0.034	-0.055	-0.077	-0.100	-0.078	-0.115	-0.058	-0.114
Cold	0.019	0.305	0.016	-0.065	-0.016	0.099	-0.033	-0.040	-0.077	-0.154
Difference	-0.063	-0.244	-0.050	0.010	-0.061	-0.199	-0.046	-0.075	0.019	0.040
t-stat	-3.072	-3.794	-0.785	0.155	-1.021	-3.465	-0.853	-1.144	0.448	1.190
Panel E: Carhart 4-Factor Alpha										
Hot	-0.055	0.011	-0.038	-0.044	-0.090	-0.098	-0.066	-0.100	-0.072	-0.107
Cold	0.012	0.239	0.013	-0.021	-0.040	0.064	0.021	-0.075	-0.082	-0.121
Difference	-0.066	-0.228	-0.051	-0.022	-0.050	-0.162	-0.087	-0.025	0.010	0.014
t-stat	-3.490	-3.852	-0.837	-0.332	-0.911	-3.010	-1.742	-0.388	0.255	0.492

Table A.4: Regressions of Post-Entry Fund Performance on Hot Style Dummy Variable (1982–2015)

This table reports results of regressions of fund performance in the m months immediately following its entry on a dummy variable that equals one if the entrant fund belongs to a hot style category at the time of entry. The dependent variables are measured by return in excess of the value-weighted CRSP index return, the CAPM alpha, the Fama-French 3-factor alpha, and the Carhart 4-factor alpha. Each fund entry during the period of 1982–2015 contributes to one observation in the regressions reported here. Fund style fixed effects are included in all specifications. The t-statistics reported are calculated using standard errors clustered at style-year level.

m	Coef.	t-stat	N	Adj. Rsq.
Panel A: Return in Excess of MKT				
12	-0.059	-0.57	2,927	0.020
24	-0.053	-0.69	2,927	0.022
36	-0.073	-1.23	2,927	0.029
60	-0.106	-2.47	2,927	0.043
Panel B: CAPM Alpha				
12	-0.107	-1.06	2,927	0.017
24	-0.102	-1.33	2,927	0.019
36	-0.109	-1.84	2,927	0.025
60	-0.140	-3.22	2,927	0.038
Panel C: Fama-French 3-Factor Alpha				
12	-0.116	-1.72	2,927	0.017
24	-0.079	-1.64	2,927	0.029
36	-0.081	-2.18	2,927	0.028
60	-0.047	-1.83	2,927	0.021
Panel D: Carhart 4-Factor Alpha				
12	-0.117	-1.77	2,927	0.017
24	-0.083	-1.79	2,927	0.025
36	-0.083	-2.48	2,927	0.022
60	-0.050	-2.20	2,927	0.012

Table A.5: Regressions of Post-Entry Fund Performance on Past Style Performance (1982–2015)

This table reports results of regressions of fund performance in the m months immediately following its entry on past style performance. The dependent variables are measured by return in excess of the value-weighted CRSP index return, the CAPM alpha, the Fama-French 3-factor alpha, and the Carhart 4-factor alpha. Past style performance is measured by the value-weighted average return of all incumbent funds in the same style category in excess of the value-weighted CRSP index return in the past 24 months. Each fund entry during the period of 1982–2015 contributes to one observation in the regressions reported here. Fund style fixed effects are included in all specifications. The t-statistics reported are calculated with standard errors clustered at style-year level.

Panel A: Return in Excess of MKT				
12	-0.168	-0.87	2,927	0.023
24	-0.211	-1.35	2,927	0.032
36	-0.197	-1.55	2,927	0.041
60	-0.200	-2.29	2,927	0.057
Panel B: CAPM Alpha				
12	-0.204	-1.08	2,927	0.020
24	-0.258	-1.70	2,927	0.033
36	-0.239	-1.86	2,927	0.042
60	-0.248	-2.85	2,927	0.060
Panel C: Fama-French 3-Factor Alpha				
12	-0.307	-3.01	2,927	0.030
24	-0.262	-3.64	2,927	0.053
36	-0.211	-3.54	2,927	0.052
60	-0.113	-2.91	2,927	0.030
Panel D: Fama-French 4-Factor Alpha				
12	-0.282	-2.84	2,927	0.028
24	-0.263	-3.77	2,927	0.050
36	-0.202	-3.80	2,927	0.042
60	-0.110	-3.30	2,927	0.021

Table A.6: Regressions of Post-Entry Fund Performance Relative to Peers on Hot Style Dummy Variable (1982–2015)

This table reports results of regressions of fund performance relative to peers in the m months immediately following its entry on a dummy variable that equals one if the entrant fund belongs to a hot style category at the time of entry. The dependent variables are measured by differences in return in excess of the value-weighted CRSP index return, the CAPM alpha, the Fama-French 3-factor alpha, and the Carhart 4-factor alpha between the entrant fund and the value-weighted average of incumbent funds in the same style category. Each fund entry during the period of 1982–2015 contributes to one observation in the regressions reported here. Fund style fixed effects are included in all specifications. The t-statistics reported are calculated using standard errors clustered at style-year level.

m	Coef.	t-stat	N	Adj. Rsq.
Panel A: Return in Excess of MKT				
12	-0.113	-1.95	2,927	0.017
24	-0.092	-2.18	2,927	0.020
36	-0.086	-2.31	2,927	0.024
60	-0.048	-1.64	2,927	0.026
Panel B: CAPM Alpha				
12	-0.096	-1.79	2,927	0.023
24	-0.097	-2.36	2,927	0.030
36	-0.092	-2.56	2,927	0.035
60	-0.064	-2.23	2,927	0.032
Panel C: Fama-French 3-Factor Alpha				
12	-0.130	-2.32	2,927	0.020
24	-0.101	-2.46	2,927	0.029
36	-0.109	-3.20	2,927	0.033
60	-0.071	-2.67	2,927	0.028
Panel D: Fama-French 4-Factor Alpha				
12	-0.118	-2.16	2,927	0.021
24	-0.105	-2.56	2,927	0.031
36	-0.101	-3.02	2,927	0.034
60	-0.075	-2.84	2,927	0.027

Table A.7: Regressions of Post-Entry Fund Performance Relative to Peers on Past Style Performance (1982–2015)

This table reports results of regressions of fund performance relative to peers in the m months immediately following its entry on past style performance. The dependent variables are measured by differences in return in excess of the value-weighted CRSP index return, the CAPM alpha, the Fama-French 3-factor alpha, and the Carhart 4-factor alpha between the entrant fund and the value-weighted average of incumbent funds in the same style category. Past style performance is measured by the value-weighted average return of all incumbent funds in the same style category in excess of the value-weighted CRSP index return in the past 24 months. Each fund entry during the period of 1982–2015 contributes to one observation in the regressions reported here. Fund style fixed effects are included in all specifications. The t-statistics reported are calculated using standard errors clustered at style-year level.

m	Coef.	t-stat	N	Adj. Rsq.
Panel A: Return in Excess of MKT				
12	-0.164	-1.84	2,927	0.018
24	-0.165	-2.68	2,927	0.024
36	-0.144	-2.27	2,927	0.029
60	-0.097	-2.06	2,927	0.030
Panel B: CAPM Alpha				
12	-0.128	-1.55	2,927	0.024
24	-0.168	-2.89	2,927	0.036
36	-0.151	-2.53	2,927	0.041
60	-0.117	-2.65	2,927	0.038
Panel C: Fama-French 3-Factor Alpha				
12	-0.216	-2.51	2,927	0.025
24	-0.207	-3.84	2,927	0.040
36	-0.197	-4.01	2,927	0.045
60	-0.140	-3.74	2,927	0.039
Panel D: Fama-French 4-Factor Alpha				
12	-0.186	-2.16	2,927	0.024
24	-0.222	-3.88	2,927	0.046
36	-0.191	-3.85	2,927	0.048
60	-0.144	-3.81	2,927	0.039

Table A.8: Regressions of Post-Entry Entrant Performance on Hot Style Dummy Variable: Inferences with Different Clustering Methods (1991–2015)

This table reports t-statistics calculated with different clustering methods for the regressions of fund performance in the m months immediately following its entry on hot style dummy variable.

m	Coef.	t-stat				N	Adj. Rsq.
		Style x Year	Robust	Year	Style		
Panel A: Return in Excess of MKT							
36	-0.071	-1.13	-2.64	-0.71	-1.39	2,801	0.029
60	-0.107	-2.34	-5.11	-1.44	-2.88	2,801	0.042
Panel B: CAPM Alpha							
36	-0.108	-1.70	-4.27	-1.06	-1.85	2,801	0.024
60	-0.143	-3.08	-7.20	-1.95	-3.20	2,801	0.038
Panel C: Fama-French 3-Factor Alpha							
36	-0.075	-1.88	-3.43	-1.33	-1.81	2,801	0.026
60	-0.041	-1.50	-2.40	-1.18	-1.64	2,801	0.016
Panel D: Carhart 4-Factor Alpha							
36	-0.078	-2.18	-3.81	-1.49	-2.21	2,801	0.018
60	-0.045	-1.89	-2.78	-1.53	-2.61	2,801	0.008

Table A.9: Regressions of Post-Entry Entrant Performance on Past Style Performance: Inferences with Different Clustering Methods (1991–2015)

This table reports t-statistics calculated with different clustering methods for the regressions of fund performance in the m months immediately following its entry on past style performance.

m	Coef.	t-stat				N	Adj. Rsq.
		Style x Year	Robust	Year	Style		
Panel A: Return in Excess of MKT							
36	-0.202	-1.55	-4.58	-1.01	-1.51	2,801	0.042
60	-0.204	-2.28	-6.44	-1.44	-2.28	2,801	0.058
Panel B: CAPM Alpha							
36	-0.246	-1.87	-5.82	-1.21	-1.75	2,801	0.044
60	-0.254	-2.87	-8.24	-1.81	-2.95	2,801	0.062
Panel C: Fama-French 3-Factor Alpha							
36	-0.209	-3.33	-6.13	-2.61	-2.23	2,801	0.047
60	-0.108	-2.64	-4.55	-2.09	-1.90	2,801	0.024
Panel D: Carhart 4-Factor Alpha							
36	-0.199	-3.56	-6.22	-2.69	-2.68	2,801	0.038
60	-0.105	-3.02	-4.61	-2.43	-2.77	2,801	0.016

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